Time-Series and Cross-Sectional Momentum in the Cryptocurrency Market: A Comprehensive Analysis under Realistic Assumptions*

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Abstract

Prior studies on cryptocurrency momentum ignore important real-world considerations and inadequately assess its performance. We analyze time-series and cross-sectional momentum addressing these issues. When appropriately assessed, *e.g.*, accounting for transaction costs and daily price fluctuations, many momentum portfolios are liquidated and many with statistically significant returns earn insignificant profits. The t-test of the mean return is insufficient to test profitability. Evidence of time-series momentum is strong, whereas evidence of cross-sectional momentum is weak. The momentum effect is concentrated among winners. Losers often rebound and inflict significant losses. Overreaction is a likely cause of momentum, but what drives overreaction is unclear.

Keywords: Cryptocurrency; Time-series momentum; Cross-sectional momentum; Liquidation risk; Overreaction.

JEL Classification: G10, G11, G12.

1 Introduction

Cryptocurrency is different from traditional assets in many aspects, such as the decentralized consensus mechanism, lack of fundamentals, and high volatility. With its unique features and growing importance as an alternative asset, it has gained popularity among academic researchers for

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the past few years. Social Science Research Network (SSRN) has a special section on cryptocurrency, which contains more than 2,000 papers.[1] Since cryptocurrencies cannot be valued via a traditional method used in the equity market, several studies have proposed new valuation models: see, *e.g.*, Bhambhwani et al. (2019); Cong et al. (2021); Liu and Tsyvinski (2021); Sockin and Xiong (2023); Biais et al. (2023). Still, there is wide disagreement about the fundamental value of a cryptocurrency or whether it has a value at all. With such a lack of fundamentals and divided options, investors are prone to overreact to news or tweets. Some overreactions may last longer than others and cause a momentum effect.

The opinion on the existence of momentum in the cryptocurrency market is divided, perhaps due to different sample selection criteria, different look-back and holding periods, and different test methods. Since the history of the cryptocurrency market is short, small changes in the empirical design can produce significantly different results. Moreover, many studies disregard important real-world considerations and inadequately assess portfolio performance. For instance, all the studies we review ignore interim price fluctuation during portfolio holding, which significantly underestimates liquidation risk. Most studies ignore transaction costs. The majority of the studies assess the existence of momentum or its profitability via a regression analysis or solely based on the t-test of the mean return. Cryptocurrencies are highly volatile and jump and crash frequently. When returns are fat-tailed, the linear approximation of log returns is no longer valid and a portfolio can earn a negative profit even when the mean return is statistically significantly positive. Hence, examining only the mean return does not provide sufficient information about the profitability of a momentum strategy.

New technologies, *e.g.*, the non-fungible token (NFT) and the decentralized autonomous organization (DAO), have emerged. There have been extreme events in the recent cryptocurrency market, such as the Terra-Luna crash and the bankruptcy of FTX. The pandemic has also witnessed unusual behaviors of the financial market. Given the short history, including recent data may give results that are completely different from earlier findings.[2] In addition, rumors among investors are that it has become more and more difficult to earn profits using momentum-based strategies.

Considering these circumstances, a more rigorous test of momentum is in order. Hence, we aim to comprehensively analyze momentum in the cryptocurrency market using up-to-date data and under realistic assumptions, and provide a more definitive answer as to the existence of momentum

[1] `https://www.ssrn.com/index.cfm/en/Cryptocurrency/`.

[2] While cryptocurrency data is usually available from 2014, there are only a handful of liquid coins until 2016.

and its underlying mechanism.

Since the seminal work of Jegadeesh and Titman (1993), momentum has been tested on diverse asset classes and from different aspects: *e.g.*, Gutierrez and Kelley (2008); Menkhoff et al. (2012); Asness et al. (2013); Jostova et al. (2013). Moskowitz et al. (2012) introduce the notion of time-series momentum and provide evidence supporting its existence in various markets. In the cryptocurrency market, Yang (2019) observes a momentum effect that remains significant even after controlling for market and size. Liu et al. (2020) report that a momentum-based long-short portfolio generates profits, and the profits are higher when coins are equally-weighted than value-weighted. Liu and Tsyvinski (2021) provide evidence of time-series momentum. They find that the current market return predicts future market returns up to eight weeks ahead. Liu et al. (2022) show that cross-sectional momentum strategies with one-, two-, three-, four-, and one-to-four-week look-back periods generate significantly positive returns. Meanwhile, other studies dispute the presence of momentum in the cryptocurrency market. Grobys and Sapkota (2019) find that one-, one-to-six-, and one-to-twelve-month cross-sectional momentum strategies do not generate significant profits, while times-series momentum strategies generate marginally significant profits. Dong et al. (2022) report that a one-to-six-month momentum portfolio does not yield statistically positive returns, whereas a one-month reversal portfolio does.

We conduct a comprehensive analysis of both time-series and cross-sectional momentum in the cryptocurrency market. We differentiate our study from the extant literature by accounting for important real-world factors and assessing the performance of a momentum strategy more accurately. As per real-world considerations, we estimate transaction costs using actual fees and tick sizes, and slippages calculated from actual trading data. We include only large and liquid coins in the sample to ensure that the coins are tradable. Furthermore, we test momentum strategies using only the coins listed on the Binance futures market as coins can be short-sold only in a futures market. We also account for the margin mode, which determines when a portfolio or a position is deemed liquidated.

To assess the performance more accurately, we mark-to-market portfolios daily regardless of their holding periods. Given the large soars and plunges of coins, ignoring interim fluctuations significantly underestimates liquidation risk. In our empirical analysis, many portfolios are liquidated during the sample period, which cannot be detected when interim price changes are ignored. We demonstrate that when the price is volatile and jumps, the usual t-test of the mean return is an inappropriate test of profitability and propose to use a t-test of the mean log return. Many portfolios with positive mean returns indeed earn negative profits in our study. We robustify our analysis by assuming that the investment is distributed evenly over the holding period. Due to the relatively short sample period, the rebalancing day, *e.g.*, every Monday, has a nontrivial effect on the empirical results and can potentially be exploited to obtain favorable outcomes.

We test cryptocurrency momentum using coins with a market capitalization of at least 1 million USD and a daily trading volume of at least 1 million USD, for the sample period from December 2013 to August 2023. We examine various look-back and holding periods ranging from one day to 56 days and identify optimal combinations of the two via regression. The selected pairs of look-back and holding periods are used to construct momentum strategies, which we analyze thoroughly.

We find strong evidence of time-series momentum. A strategy that buys the market when its look-back period return falls within the top third of the historical returns outperforms the market for a wide range of look-back and holding periods. The strategy performs best when the look-back period is twenty-eight days and the holding period is five days: It yields a Sharpe ratio of 1.51, while the market portfolio yields 0.84. The superior performance mainly results from reduced downside risk. The strategy holds a long position only when the market is bullish and defends well against market downturns. In contrast, a strategy that sells the market when the market falls always yields negative profits, implying that time-series momentum is concentrated in a bullish market. Time-series momentum performs comparably across different size, volume, and overreaction groups. Since coins lack fundamentals, they tend to move in tandem following the movement of Bitcoin. Such collective behavior results in similar time-series momentum performance across different types of coins. Liu et al. (2022) three-factor model cannot explain time-series momentum.

Regarding the driver of momentum, we find evidence supporting the overreaction mechanism. A factor related to overreaction explains much of the time-series momentum premium. Cross-sectionally, we do not observe a noticeable difference between high-attention coins and low-attention coins: A time-series momentum portfolio formed of high-volume coins performs comparably with that of low-volume coins. Our findings contradict the argument of Liu and Tsyvinski (2021). They observe that low-attention coins exhibit stronger time-series momentum and, consequently, attribute the time-series momentum effect to underreaction. They, however, compare only ten well-known coins.

In contrast to time-series momentum, evidence of cross-sectional momentum is weak. Among 21 cross-sectional momentum portfolios of selected look-back and holding periods, five are liquidated during the sample period and only six outperform the market. The best strategy with a look-back period of fourteen days and a holding period of seven days earns a Sharpe ratio of 1.28, while the market earns a Sharpe ratio of 1.01. The profit of a cross-sectional momentum strategy mostly originates from the long leg. The short leg is exposed to high jump risks and incurs losses. Even though we only include relatively large and liquid coins, extreme returns are not rare. Ten portfolios yield a positive mean return with a t-statistic greater than 2.0, but only three of them have a mean log return with a t-statistic greater than 2.0. Moreover, six portfolios with a positive mean return are either liquidated or earn a negative profit. These results demonstrate the inadequacy of the mean return as a long-term profitability indicator.

Cryptocurrency momentum has very different characteristics compared to equity momentum. In the equity market, the momentum profit originates mainly from the short leg and small stocks. In contrast, it originates mainly from the long leg and large coins in the cryptocurrency market. Except for a few largest coins, the majority of the coins exhibit reversal rather than momentum. Momentum (among large coins) or reversal (among small coins) effects are easily observed among winners, but these effects do not appear clearly among losers. One exception is a strong long-term reversal effect among large losers.

Regarding the underlying mechanism of cross-sectional momentum, we do not find a single mechanism that is consistent with our findings. Overreaction is a likely cause of momentum: We observe long-term reversal; the cryptocurrency market is dominated by retail investors, who are more prone to overreaction; the momentum effect is stronger among winners with a higher continuing overreaction measure; the sheer fact that three-digit returns are not uncommon is clear evidence of overreaction. However, the overreaction period varies across coins, and overreaction followed by correction can also cause reversal for the same holding period: Winners with a higher trading volume tend to fall in the short run; winners in the highest overreaction group perform poorly; losers frequently rebound.

Our findings do not support the attention-based explanation (Peng and Xiong, 2006; Andrei and Hasler, 2015; Liu et al., 2022). A momentum portfolio formed of higher volume coins underperforms that of lower volume coins. In particular, the performance of the long leg, where the momentum effect is concentrated, worsens monotonically with volume. A long-short portfolio formed of coins that receive unusually high attention performs even worse. We also do not find evidence that the momentum strategy performs better during a high-attention period.

A plausible explanation for the difference in the performance of large and small coins is the different composition of investors. Speculators and retail investors prefer small coins for their high volatility and potential jackpot returns, whereas institutional investors and long-term investors choose major coins for their liquidity and relative stability. Speculators trade more frequently to realize profits. Such activities can make the price continuation of small coins short-lived and cause reversal. The cryptocurrency's price dynamics are uniquely influenced by its close ties to online communities and real-time information flow via social media. Minor coins are more susceptible to sentiment changes and their price continuation and reversal are far less predictable, making it difficult to detect momentum effects in these coins.

Overall, we do find some evidence of momentum, especially in the time series. Nevertheless, it should not be forgotten that we test various pairs of look-back and holding periods and choose optimal combinations. This practice introduces a look-ahead bias. Because of the high tail risk that can potentially wipe out the entire portfolio value, investors are likely to impose certain stop-loss rules, which can significantly change the characteristics of a momentum strategy. Considering these points, our findings should be regarded as an optimistic view. A short position inflicts a significant loss on momentum strategies due to large jumps. On the other hand, a long-only strategy is exposed to the high risk of the cryptocurrency market. A momentum-based long-short strategy that can generate steady, market-neutral profits appears unattainable. The maximum Sharpe ratio we obtain from a momentum strategy is about 1.5. Meanwhile, several studies obtain a Sharpe ratio greater than 2.0 in the equity market: *e.g.*, Gu et al. (2020); Han (2022). Considering the high tail risk, the small number of liquid coins, and the high dominance of a few major coins, it is difficult to argue that a cryptocurrency momentum strategy is an attractive alternative investment vehicle to institutional investors.

We contribute to the cryptocurrency literature by conducting a comprehensive analysis of momentum and unveiling its true nature. We reveal the limitations of prior studies, propose alternative testing methods, and uncover the true risk of a momentum-based strategy. We also present evidence related to the underlying mechanism of momentum, which contradicts earlier findings. By accounting for real-world considerations, we bridge the gap between theory and practice. The cryptocurrency market is still immature and fast-evolving. Although we use up-to-date data, it has only ten years of data and the period with adequate number of coins is even shorter. The conclusion of this paper may be overturned in the future when the market becomes mature and more data are accumulated. Still, the methodologies we employ should remain valid.

The rest of the paper is organized as follows. Section 2 discusses the long-term profitability of a portfolio and pitfalls of the conventional t-test of the average return when the returns are fat-tailed. Section 3 describes the sample data and the methodology employed for the empirical analysis. Section 4 and 5 run various tests respectively on time-series momentum and cross-sectional momentum. Section 6 concludes.

2 Long-term profitability of a portfolio

Let P_t denote the value (price) of a portfolio at time t. When the rate of return, $r_t = P_t/P_{t-1} - 1$, is sufficiently small, the log return, $l_t = \log(P_t/P_{t-1}) = \log(1 + r_t)$, can be approximated by r_t, and if the sample mean of $r_t,\ t = 1, \ldots, T,\ \bar{r} = \sum_{t=1}^{T} r_t/T$, is statistically significantly positive, one may conclude that the sample mean of l_t, $\bar{l} = \sum_{t=1}^{T} l_t/T = \log(P_T/P_0)$, will also be positive and the portfolio will be profitable. However, if the return is highly volatile and often involves jumps, which is the case of the cryptocurrency market, the approximation is no longer valid and the cumulative return can be negative even when the mean return is significantly positive, due to Jensen's inequality. This is a well-known fact but often disregarded because returns are usually small enough in the securities market. In the cryptocurrency market, on the other hand, three-digit returns are not rare and examining only the mean return can lead to a misleading conclusion. We investigate this point more in detail under the assumption that the price follows a geometric Brownian motion or a jump-diffusion process.

2.1 Diffusion process

Suppose P_t follows a geometric Brownian motion of the form:

$$dP_t/P_t = \mu dt + \sigma dW_t, \tag{1}$$

where μ denotes the drift, σ volatility, and W_t a standard Wiener process. The log return, $X_t = \log(P_t/P_0)$, is then given by

$$X_t = \left(\mu - \frac{\sigma^2}{2}\right) t + \sigma W_t, \tag{2}$$

and its expectation has the form

$$E[X_t] = \left(\mu - \frac{\sigma^2}{2}\right) t. \tag{3}$$

Equation (3) shows that if $\mu - \sigma^2/2 < 0$, the expected value of the portfolio converges to 0 even when μ is positive.

When returns are measured at a short interval, the sample mean $\bar{r}$ roughly estimates μ, and one would reject the null hypothesis $\mu = 0$ if the t-statistic is greater than a critical value. If both μ and σ increase by a factor of $a > 1$, $\mu - \sigma^2/2$ decreases and eventually becomes negative as a increases, but the test statistic will remain at the same level. That is, if the mean and the standard deviation are sufficiently high, there is a good chance of the long-term value converging to zero even when $\bar{r}$ is statistically significantly positive.

2.2 Jump-diffusion process

Cryptocurrency returns are skewed and fat-tailed and they might be better described by a jump-diffusion process. Following Merton (1976), we assume X_t has the distribution

$$X_t = \left(\mu - \frac{\sigma^2}{2} - \lambda k\right) t + \sigma W_t + \sum_{i=0}^{N_t} Y_i, \tag{4}$$

where N_t is a Poisson variable with the intensity parameter λ, $Y_i \sim N(\nu, \delta^2)$ is a random jump size, and $k = \exp\left(\nu + \delta^2/2\right) - 1$. The first four moments of l_t are given by (Matsuda, 2004):

$$\begin{aligned} E[l_t] &= \mu - \frac{\sigma^2}{2} - \lambda k + \lambda\nu, && (5)\\ Var[l_t] &= \sigma^2 + \lambda\delta^2 + \lambda\nu^2, && (6)\\ Skew[l_t] &= \frac{\lambda(3\delta^2\nu + \nu^3)}{\left(\sigma^2 + \lambda\delta^2 + \lambda\nu^2\right)^{3/2}}, && (7)\\ Kurt[l_t] &= \frac{\lambda(3\delta^4 + 6\nu^2\delta^2 + \nu^4)}{\left(\sigma^2 + \lambda\delta^2 + \lambda\nu^2\right)^2}. && (8) \end{aligned}$$

The second-order approximation of k yields

$$E[l_t] \approx \mu - \frac{s^2}{2} - \frac{\lambda\delta^2}{2}\left(\frac{\delta^2}{4} + v\right), \tag{9}$$

where $s^2 = \sigma^2 + \lambda\delta^2 + \lambda\nu^2$ is the variance. For the same μ and variance, the expected log return under a jump-diffusion process will be always smaller if the expected jump size ν is non-negative.[3] Otherwise, it will be smaller when $\delta^2/4 + \nu > 0$. A positive ν implies positive skewness. The kurtosis is always greater under the jump-diffusion assumption. The cross-sectional momentum portfolios we test in the empirical analysis have positive skewness. Thus, if the portfolio value follows a jump-diffusion process, *ceteris paribus*, the expected log return will be smaller and there

[3]If the parameters of the diffusion process and the jump-diffusion process are calibrated using the same data, the estimated μ and variance will be similar between the two processes: the estimates of μ will be close to $\bar{r}$ and those of the variance will be close to the sample variance of the log returns.

will be a higher chance of the long-term value converging to zero.

2.3 Simulation

Under the diffusion process, $l_t \sim N(\mu - \sigma^2/2, \sigma^2)$, and its sample mean $\bar{l}$ is expected to lie in the interval

$$\bar{l} \in \left(\mu - \frac{\sigma^2}{2} - c\frac{\sigma}{\sqrt{T}},\ \mu - \frac{\sigma^2}{2} + c\frac{\sigma}{\sqrt{T}}\right), \tag{10}$$

where c is the critical value that corresponds to a confidence level. Similarly, the sample mean of the returns $\bar{r}$ is expected to lie in the interval[4]

$$\bar{r} \in \left(\mu - c\frac{\sigma}{\sqrt{T}},\ \mu + c\frac{\sigma}{\sqrt{T}}\right). \tag{11}$$

Under the jump-diffusion process, these intervals are given by

$$\bar{l} \in \left(\mu - \frac{\sigma^2}{2} - \lambda k + \lambda\nu - c\frac{s}{\sqrt{T}},\ \mu - \frac{\sigma^2}{2} - \lambda k + \lambda\nu + c\frac{s}{\sqrt{T}}\right), \tag{12}$$

and

$$\bar{r} \in \left(\mu - c\frac{s}{\sqrt{T}},\ \mu + c\frac{s}{\sqrt{T}}\right). \tag{13}$$

When there are jumps, the variance of r_t cannot be approximated by the variance of l_t, and the interval in Equation (13) can be significantly different from the true interval. Thus, we also estimate the intervals via simulation.

We draw the intervals of $\bar{l}$ and $\bar{r}$ using the parameters estimated from the daily returns of one of the best-performing cross-sectional momentum portfolios in Section 5.2. The daily returns' mean, standard deviation, skewness, and kurtosis are respectively 0.005, 0.072, 14.442, and 466.270. The corresponding values of the daily log returns are 0.003, 0.060, 1.805, and 94.329.

For parameter estimation, we use the maximum likelihood estimates for the diffusion process: $\hat{\mu} = 0.0047$ and $\hat{\sigma} = 0.0600$. For the jump-diffusion process, we use a constrained maximum likelihood estimator as described in the Appendix. The estimates are: $\hat{\mu} = 0.0048$, $\hat{\sigma} = 0.0320$, $\hat{\nu} = 0.0510$, $\hat{\delta} = 0.3942$, and $\hat{\lambda} = 0.0163$. The Kolmogorov–Smirnov (KS) statistic is 0.1551 for the diffusion process and 0.0404 for the jump-diffusion process. Although both processes are rejected, the jump-diffusion process has a smaller statistic.

[4]We assume the time interval is sufficiently small such that the variance of r_t is approximately the same as that of l_t.

Based on these estimates, we draw the intervals for the following range of the parameters: $\mu = 0.0015a$, $\sigma = 0.0200a$ for the diffusion process, and $\mu = 0.0015a$, $\sigma = 0.0100a$, $\nu = 0.0150a$, $\delta = 0.1095a$, $\lambda = 0.0150$ for the jump-diffusion process, where $a \in [1, 10]$. These parameters generate the same variance under both processes and pass through the estimated parameters. The skewness and the kurtosis of the jump-diffusion process are independent of a and remain the same at 1.615 and 105.729. The sample period T and the confidence level are respectively set to 1,000 days and 95%.

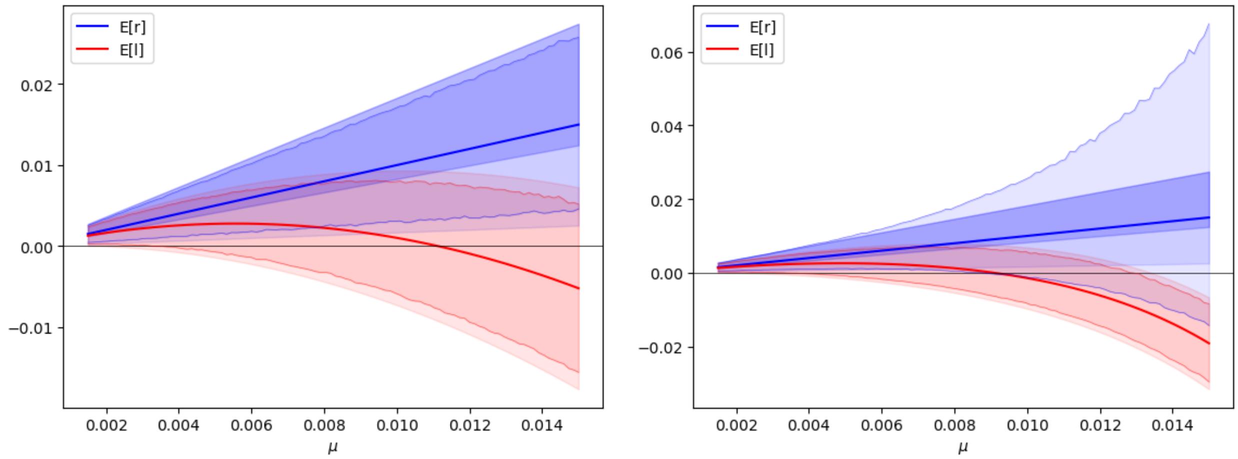
Figure 1 reports the simulation results, where panels (a) and (b) display the intervals under the diffusion process and the jump-diffusion process, respectively. The shaded regions display the intervals: the regions with a smooth boundary are obtained from Equations (10) to (13), and the regions with a wiggly boundary are obtained from simulations with 10,000 iterations. The dark blue region is where $\bar{r}$ is statistically significantly positive.

The graphs reveal several important points. First, as μ increases, the expected log return, and therefore the expected profit, becomes negative, whereas the chance of rejecting the null hypothesis remains the same. The expected log return turns negative when $\mu > 0.011$ under the diffusion process and when $\mu > 0.009$ under the jump-diffusion process. For the same μ and variance, the expected log return is lower under the jump-diffusion assumption, and the gap widens as μ increases. If the portfolio value follows a jump-diffusion process, it is more likely to converge to 0 while the mean return indicates a profit. Second, under the jump-diffusion process, the interval of $\bar{r}$ is significantly wider and the t-test on $\bar{r}$ becomes almost meaningless especially when μ is high. Third, even when $\bar{l}$ is positive, there is a nontrivial chance of its true mean being negative. Put together, in a highly volatile market such as the cryptocurrency market, examining the simple mean return and the cumulative return is not sufficient. To test the long-term profitability adequately, it is necessary to check the significance of log returns.

3 Data and methodology

3.1 Data

Our data include all available cryptocurrencies in CoinMarketCap. CoinMarketCap collects data from over 200 exchanges and provides daily data on opening, closing, high, and low prices, trading volume, and market capitalization, all denoted in USD. CoinMarketCap includes a cryptocurrency in its dataset when it satisfies the following requirements: It has a functional website and block



(a) Diffusion

(b) Jump-diffusion

Figure 1: Intervals of sample mean returns and sample mean log returns.

explorer; is traded publicly on at least one major exchange; and provides a representative from the project to communicate. It deports cryptocurrencies that have attempted to manipulate their prices or circulating supplies. The final dataset includes both active and inactive cryptocurrencies and therefore is free of survivorship bias. The trading volume has been available since December 28, 2013, and our sample starts on this date and ends on August 28, 2023.

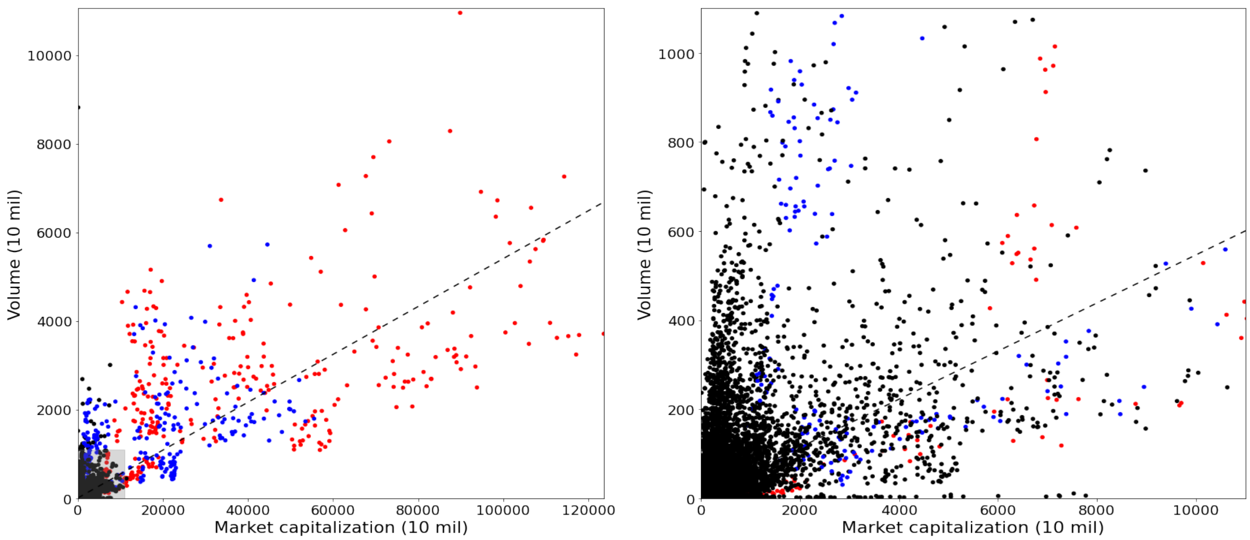
The market capitalization provided by CoinMarketCap is the product of price and circulating supply. According to CoinMarketCap, circulating supply represents the number of coins that are circulating in the market and not held by private investors or under stacking. CoinMarketCap argues that circulating supply is a more appropriate metric than total supply for market capitalization. We independently calculate market capitalization using both definitions of supply and also find that the market capitalization based on total supply is not reliable.[5] Therefore, we use the market capitalization provided by CoinMarketCap that utilizes circulating supply.

The market capitalization data includes some negative values without any description, which we opt to treat as missing values. We also identify events such as splits that are not reflected in the CoinMarketCap data and adjust the affected prices manually. The coins that are manually adjusted can be found in the Internet Appendix (IA).

While most prior studies employ market capitalization as the sole data filtering criterion, *e.g.*, Liu and Tsyvinski (2021); Liu et al. (2022), some large cryptocurrencies suffer from low liquidity and may not be tradable without significantly impacting the market. To see the relationship

[5]A comparison of the two methods is reported in the Internet Appendix (IA).

between market capitalization and trading volume, we draw in Figure 2 a scatter plot of market capitalization against trading volume. Figure 2 (a), the scatter plot of all coins including Bitcoin (red) and Ethereum (blue), suggests a linear relationship between market capitalization and trading volume. The correlation coefficient is 0.813. However, once we zoom in on the area where most coins lie (Figure 2 (b)), it becomes clear that there are many small coins with large trading volumes, and vice versa.



(a) All coins

(b) Excluding major coins

Figure 2: Market capitalization vs. trading volume

This figure displays scatter plots of market capitalization and trading volume. The market capitalization and trading volume are 30-day averages. Red and blue dots respectively denote Bitcoin and Ethereum. Panel (b) magnifies the shaded area in panel (a).

Since some coins have extremely low liquidity relative to their size, we consider three data filtering criteria for our analysis: 1) market capitalization of 1 million USD; 2) trading volumes of 1 million USD; and 3) a combination of both.[6] The filters are applied to 30-day moving averages to reduce the variation of the coins in the sample over time.

Table 1 reports the number of coins in the sample after applying the filters. Without any filter, the number of coins increases rapidly, especially in recent years, and reaches almost 9000 in 2023. However, the number of coins with a market capitalization of at least 1 million USD (column ‘M’) remains stable at around 1300 over the past three years, which implies that most newly minted coins during this period do not meet the minimum market capitalization requirement. When coins

[6]The trading volume provided by CoinMarketCap is an aggregate value from all exchanges. Therefore, the trading volume of the coins that pass the volume filter can be significantly lower than 1 million USD in each exchange.

are filtered using both market capitalization and trading volume (column 'M&V'), the number is further reduced by more than half. For instance, in 2023, the number of coins obtained from the 'M' filter, 1332, is roughly 2.8 times greater than that from the 'M&V' filter, 471. On the other hand, the divergence between the 'V' column (trading volume filter) and the 'M&V' column is relatively small, which implies that trading volume is the binding condition. Consequently, we apply both market capitalization and volume filters to ensure that the portfolio strategies we test are implementable.

Table 1: Effects of filtering methods on the sample size

This table reports the number of coins, total market capitalization, and trading volume after applying different filtering methods. 'None', 'M', 'V', and 'M&V' respectively denote no filter, size filter (minimum 1 million USD), volume filter (minimum 1 million USD), and size and volume filter. The figures are annual averages.

	Number				Market cap (100 mil)				Volume (100 mil)			
Year	None	M	V	M&V	None	M	V	M&V	None	M	V	M&V
2014	287	25	3	2	75.21	74.47	64.27	63.97	0.36	0.35	0.29	0.28
2015	483	28	3	2	45.18	44.73	41.35	40.67	0.41	0.39	0.38	0.38
2016	499	52	5	4	107.38	106.47	101.40	100.61	1.23	1.17	1.13	1.12
2017	579	169	54	43	1259.97	1238.87	1227.70	1214.64	53.33	51.69	51.99	51.32
2018	711	448	192	147	2967.85	2946.89	2906.97	2882.72	146.44	143.65	144.24	142.92
2019	1080	553	213	160	2079.26	2073.15	2043.33	2033.46	365.07	361.38	362.55	360.45
2020	1559	709	317	240	3173.84	3151.09	3100.53	3080.29	748.57	739.67	743.33	738.43
2021	3102	1269	832	562	18573.99	18379.11	18278.61	18210.29	1618.12	1564.21	1603.50	1561.90
2022	6571	1382	883	544	12055.43	12024.80	11860.31	11797.77	5295.64	804.92	5273.48	802.65
2023	8967	1332	694	471	10310.87	10283.47	10125.91	10055.93	446.00	416.43	434.08	414.18

We further exclude 96 coins from our sample that are categorized as stablecoins. Stablecoins are designed to be pegged to their underlying assets, typically USD. As a result, the price of stablecoins depends on their solvency and moves little unless their credibility is challenged. Therefore, it is proper to remove stablecoins from the sample to capture the true effect of momentum in the cryptocurrency market. The list of stablecoins is reported in the Internet Appendix.

Table 2 presents the performances of the market portfolio, equal-weight portfolio, Bitcoin, Ethereum, and NASDAQ 100. The market portfolio is defined as the value-weighted portfolio of all coins in the sample. The table demonstrates substantial returns of cryptocurrencies with the market, Bitcoin, and Ethereum yielding annualized mean returns of 62.37%, 63.13%, and 146.05%, respectively. Yet, they also record maximum drawdowns (MDDs) of 89.1%, 83.4%, and 94.0%. It is crucial to understand that while the cryptocurrency market offers potentially high returns, they are inherently paired with substantial risks, as evidenced by the elevated standard deviations and maximum drawdowns. As a consequence, the Sharpe ratios of the cryptocurrency market and Bitcoin, 0.85 and 0.88, respectively, are even lower than that of NASDAQ 100, which is 0.96.

Table 2: Performance of cryptocurrencies

This table reports the performance of the market portfolio (MKT), equal-weight portfolio (MKT-EW), Bitcoin, Ethereum, and NASDAQ 100. 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). All values are calculated using the daily returns during the sample period from December 28, 2013 to August 28, 2023, except for Ethereum, whose sample starts on August 8, 2015.

	Mean	Std	Sharpe	Cum	MDD
MKT	62.37	73.63	0.85	2695.9	89.1
MKT-EW	75.60	88.30	0.86	2970.3	97.0
Bitcoin	63.13	72.05	0.88	3451.5	83.4
Ethereum	146.05	113.22	1.29	59509.8	94.0
NASDAQ 100	25.43	26.43	0.96	325.8	35.6

Figure 3 plots the total market capitalization, the total trading volume, and the number of coins in our sample. The number of coins starts at 5 on the first day of the sample, peaks at 784 in December 2021, and ends at 433 on the last day.[7] The total market capitalization peaks in early 2022 reaching almost 3 trillion USD, then drops significantly and remains at around 0.95 trillion USD.

The cryptocurrency market is a highly concentrated market, where only a couple of coins, Bitcoin and Ethereum in particular, dominate. The market dominance of Bitcoin and Ethereum reaches its highest at 96.2% in 2016 and the lowest at 48.9% in 2018. Across the sample period, the average market dominance of the two coins stands at 79.0%.

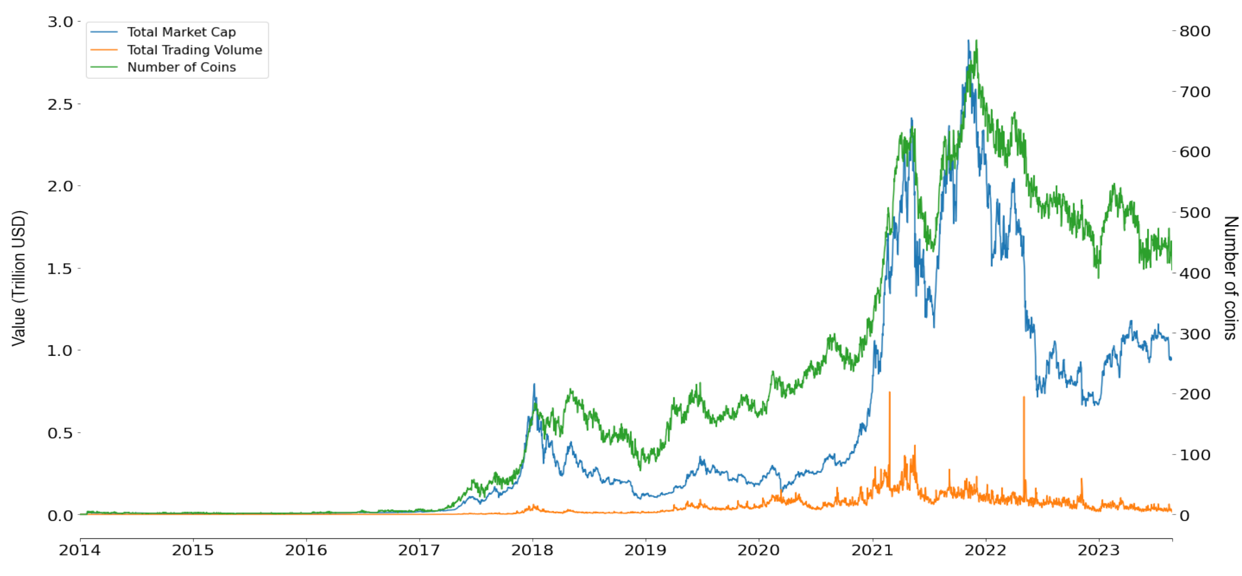


Figure 3: Cryptocurrency market overview

[7]The number of coins in 2014 in Table 1 is 2 not 5. This discrepancy arises because market capitalizations have declined throughout 2014 due to prolonged price drops.

3.2 Methodology

3.2.1 Procedure

We analyze both time-series and cross-sectional momentum in the cryptocurrency market. We initially conduct statistical analyses of momentum characteristics employing percentile rank regressions. Through the regression analysis, we examine various pairs of look-back and holding periods ranging from one day to 56 days and identify optimal combinations of the two. Next, we construct momentum portfolios using the chosen look-back and holding period pairs and evaluate them thoroughly. For time-series momentum, we test strategies trading the market portfolio and for cross-sectional momentum, we test coin-level long-short strategies. We run diverse tests to identify the driver of momentum and to check the robustness of our findings.

3.2.2 Portfolio formation

We use value-weighted portfolios for the main analysis, but we also examine other portfolio construction methods: volume-weight, equal-weight, capped-value-weight, and capped-volume-weight. Given the high dominance of major coins, a value-weighted portfolio can be concentrated on a couple of major coins and the findings from it may not represent the entire market. By capping the weight, we can reduce the dominant effects of major coins. In a capped-value-weighted portfolio, the weights of the largest 5% coins are capped at the 5% value. Large coins with low trading volume may not be a viable investment vehicle even for a moderately large portfolio, especially when their weights are determined based on their size. From a feasibility point of view, weighting the coins based on their trading volume could be more realistic. Therefore, we also consider volume-weighted and capped-volume-weighted portfolios. The capped-volume-weighted portfolio is similarly defined to the capped-value-weighted portfolio.

3.2.3 Transaction costs

An important aspect of real-world investment is transaction costs. We assume a transaction cost of 15 basis points (bps) for every trade. At the time of writing this article, Binance, the leading cryptocurrency exchange, charges a fee of 10 bps to regular users in the spot market and 4.5 bps in the futures market, and the average tick size relative to the price is 3.26 bps in the futures market.[8] From 15,661,698 records of actual market orders in the Binance futures market during the period

[8]Binance runs a VIP program and an investor with a large trading volume can get discounts on the fees. The fees applied to a regular user are the upper limits.

from June 24, 2023 to August 20, 2023, we find that the minimum, maximum, and average slippage per coin are respectively 0.01, 11.81, and 1.53 bps.[9] The order sizes are very small compared to the daily trading volume: 56 USD or 0.02% of the daily trading volume on average. Larger orders would have a bigger impact on the market resulting in greater slippages. Binance offers one of the lowest fees in the market and the fees have decreased over time. Given these circumstances, we consider a transaction cost of 15 bps a reasonable estimate (or perhaps closer to the lower limit) of the actual transaction costs. We analyze the impacts of transaction costs on portfolio performance to lend more solidity to our analysis.

3.2.4 Marking to market

Portfolios are marked to market daily regardless of the holding period. Cryptocurrencies often experience soars and plunges within a short period, and ignoring interim price fluctuations during the holding period leads to an underestimation of short-term volatility and liquidation risk. For example, take the period of the dramatic rebound of Terra Luna. After plummeting for nine consecutive days culminating in a total loss of 99.99%, it surged by 349.75% on May 14, 2022. Such an extreme turnaround can inflict considerable losses on short positions, potentially leading to portfolio liquidation. However, the weekly return of Luna on that week still displays a 99.99% drop. The magnitude of the decline overshadows the rebound and the risk of liquidation would not be captured if daily fluctuation is ignored. Similarly, on June 7, 2022, Unifi Protocol DAO (UNFI) surged over 1,000% and ended the day at 432.78%, only to sharply decline by 55.44% the next day. A short position of UNFI on July 7 could have liquidated the entire portfolio. Yet, the return of the week is a rather moderate gain of 210.85%, which obscures the true risk.

In our sample, there are three occurrences of five consecutive days of price increase followed by a drop of 50% or more the subsequent day; 136 occurrences of five consecutive days of price decline followed by a hike of 50% or more the next day. These observations demonstrate the extreme volatility of the cryptocurrency market and underscore the importance of daily mark-to-market to accurately assess the performance of momentum strategies.

We use daily close prices to mark-to-market, which can be significantly different from daily highs and lows. Thus, our approach, while more accurate than ignoring interim fluctuations, still underestimates liquidation risk. An important implication of such extreme price movements is that most investors would not be able to bear huge short-term losses and are likely to impose certain

[9] The average slippages of all coins can be found in the Internet Appendix.

types of stop-loss rules, which can change the characteristics of a momentum strategy in a nontrivial fashion. Therefore, even if a naïve test of a momentum strategy indicates a significant profit, the actual profitability cannot be guaranteed and the results should be interpreted with caution.

Table 3 compares daily returns with weekly returns. In panel (a), 'MKT' denotes the market portfolio, and the values in 'Coins' are the averages of the values obtained from individual coins. The daily returns of the market and individual coins have a much higher kurtosis, 6.81 and 23.83, respectively, compared to the weekly returns, 1.61 and 14.47, which implies fatter tails of daily returns. The average Sharpe ratio of individual coins obtained from daily returns, 0.18, is lower than the average Sharpe ratio obtained from weekly returns, 0.24. Panel (b) reports the distribution of all coins' daily returns. It reveals cryptocurrencies' extremely volatile nature, as evidenced by the minimum return of -99.61% and the maximum return of 9187.42%. As reported in the empirical analysis, the positively skewed and fat-tailed distribution of coin returns often causes large losses from short positions, making it difficult to construct a steady long-short strategy. In an unreported analysis, we compare daily mark-to-market with weekly mark-to-market and find that weekly mark-to-market overestimates the Sharpe ratio and misses liquidation events that are captured under daily mark-to-market.

Table 3: Distribution of cryptocurrency returns

This table reports the summary statistics of daily and weekly returns. In panel (a), 'MKT' denotes the market portfolio and 'Coins' denotes individual coins: The values are calculated for each coin and averaged. Values in parentheses are daily values converted to weekly. Panel (b) reports the distribution of all coins' daily returns. The mean (Mean), standard deviation (Std), and the percentile values of the returns are in percentage.

		Mean	Std	Sharpe	Skew	Kurt
MKT	Daily	0.17 (1.18)	3.85 (10.19)	0.04 (0.12)	-0.53	6.81
	Weekly	1.20	10.54	0.11	0.13	1.61
Coins	Daily	0.88 (6.14)	13.03 (34.47)	0.07 (0.18)	2.02	23.83
	Weekly	9.71	40.65	0.24	1.98	14.47

(a) Summary statistics of market and coin returns

Percentile	Min	0.1%	1%	5%	10%	50%	90%	95%	99%	99.9%	Max
Return	-99.61	-37.47	-19.64	-11.01	-7.72	-0.18	7.80	12.51	29.09	81.16	9187.42

(b) Distribution of daily returns of all coins

3.2.5 Day-of-the-week effects

Given the relatively short sample period, the start date of a backtest can have a nontrivial impact on the empirical results. If a strategy has a holding period of a week, rebalancing the portfolio every Monday can yield a significantly different result from rebalancing every Sunday. French (1980) finds equity returns on Mondays are significantly lower than those on the other weekdays. This so-called Monday effect is a well-documented equity market anomaly. Fishe et al. (1993) suggests that this anomaly is caused by the reflection of negative news over the weekend on Monday's returns. Although the cryptocurrency market operates 24/7, studies find a day-of-the-week effect. In contrast to the equity market, Caporale and Plastun (2019) and Baur et al. (2019) report that Bitcoin's Monday returns are significantly higher than the returns on the other days.

To address the day-of-the-week effect, we conduct the empirical analysis as follows. For a time-series momentum strategy, we run independent tests starting on each day of the holding period and report the average performance. For instance, if a strategy's holding period is three days, we test the strategy three times starting on the first three days of the sample period. When the holding period is longer than a week, we test the strategy seven times starting on different days of the week. For a cross-sectional momentum strategy, we assume that we invest $1/k$ of the wealth on each day, where k is the holding period. We treat the k investments as if they are in separate accounts, *i.e.*, a profit from one portfolio is not transferred to another, and if a portfolio's loss exceeds 100%, it is liquidated and the loss is not propagated to the other portfolios. We do not use the same method for a time-series momentum strategy because it trades only when a momentum condition is met, unlike a cross-sectional momentum strategy that trades on every rebalancing day. These methods allow us to neutralize the day-of-the-week effect and render more robust results. As we show later, investing 100% on a particular day of the week yields very different results depending on the choice of the day.

3.2.6 Leverage and margin mode

In the cryptocurrency market, short positions are typically taken via perpetual futures (swaps). Perpetual futures are futures contracts with an indefinite maturity, and their prices are synced with the spot prices through a funding fee mechanism.[10] Cryptocurrency exchanges demand a margin for both long and short positions and opening a long position for 100 USD and a short position for 100 USD requires a margin of 200 USD. Therefore, in order to invest 100% of the wealth in each

[10]If the futures price is higher than the spot price, long positions pay a fee to short positions, and vice versa.

leg of a long-short portfolio, we assume a leverage of 2. A consequence of this assumption is that the maximum amount a strategy can invest is limited to a rather small value, possibly too small for institutional investors. This is because exchanges limit the maximum amount a leveraged position can hold, and the limit is stricter for smaller, less liquid coins. Thus, we also test strategies assuming no leverage and investing half of the wealth in each leg. Under this assumption, the portfolio sacrifices potential profits but also has a lower chance of liquidation.

Another point we need to consider is when the portfolio is deemed liquidated. Cryptocurrency exchanges usually offer two types of margin mode in the futures market.[11] Under the cross-margin mode, the entire account balance is utilized to margin all open positions and gains from profitable positions counterbalance losses from the others. The margin level is determined by the combined value of the assets and obligations within the cross-margin account, and in the event of liquidation, every position in the account is impacted. Investors prefer the cross-margin mode for its mutual support. Under the isolated-margin mode, a specific collateral amount backs each trade and every position functions independently. Thus, if the margin level of a position drops below the maintenance margin, the position is liquidated but the other positions are not affected.

Liquidation occurs more frequently under the isolated-margin mode, but the loss is limited to the value of the liquidated position. On the other hand, liquidation is less likely under the cross-margin mode, but once it happens, it can wipe out the entire portfolio value. For the main analysis, we assume the cross-margin mode with 0 maintenance margin. In reality, the maintenance margin is greater than 0 and there is a higher chance of liquidation. Later, we also explore the isolated-margin mode.

4 Time-series momentum

4.1 Regression analysis

Moskowitz et al. (2012) introduce the notion of time-series momentum and explore its profitability in equity index futures, commodity futures, bond futures, and currency futures. Unlike the traditional cross-sectional momentum that compares returns cross-sectionally, time-series momentum makes an investment decision based on the previous returns of an asset itself. Moskowitz et al. (2012) find that time-series momentum and cross-sectional momentum are similar but different from each other.

[11] A detailed description of the margin modes in Binance can be found in the link: https://www.binance.com/en/blog/margin/binance-margin-differences-between-the-new-isolated-margin-mode-and-cross-margin-mode-421499824684900602.

Neither momentum can fully explain the other. Lim et al. (2018) apply time-series momentum to the US equity market and observe its existence since 1927. They find that time-series momentum is dependent on the market state, information related to individual stocks, and investment sentiment. In the cryptocurrency market, Liu and Tsyvinski (2021) demonstrate the presence of time-series momentum. They regress a future cryptocurrency market return on its current return and find that the current return is statistically significant and positively correlated with the future return. They also show that time-series momentum is stronger among coins with relatively low investor attention.

To develop a time-series momentum strategy, we first conduct regression analyses using different pairs of look-back and holding periods. Moskowitz et al. (2012) employ two regression models to identify time-series momentum in a monthly time frame. In one model, they regress a volatility-scaled return on a volatility-scaled past return. In the other model, the dependent variable is the same, but the independent variable is defined as the sign of the past return. We use time-seires percentile ranks of returns for the regression analysis, which is defined as follows. On day t, all the j-day past returns, $r_{t-j,t}$, $r_{t-2j,t-j}, \cdots$, are ranked and divided by the number of observations to obtain the time-series percentile rank. We opt for the percentile rank for the following reasons. First, it addresses the scaling issue. In the highly volatile cryptocurrency market, a regression using raw returns can be distorted by extreme returns. This problem can be effectively handled by re-scaling returns to a value between 0 and 1 via the percentile rank operation. Second, percentile rank provides insights into the current market state. The percentile rank of a return at any given time is determined by its relative position to the historical returns. Consequently, percentile rank serves as a representation of the current market state, with a high percentile rank indicating a bullish market and a low rank a bearish market. This information allows us to analyze how the market condition affects the performance of time-series momentum and its ability to predict returns. The regression equation has the form

$$p_{t,t+k} = \alpha + \beta p_{t-j,t} + \epsilon_t, \tag{14}$$

where $p_{t,t+k}$ denotes the time-series percentile rank of the return over t and $t+k$, $r_{t,t+k}$, and ϵ_t is an error term.

Table 4 reports the regression results using the market return, where the rows and columns respectively represent the look-back and the holding periods. The values in the table are the estimates of β and the corresponding t-statistics. For clarity, only the coefficient is reported since the constant does not provide additional insights. It is notable that all the coefficients, except for the (1, 1) pair, are positive, providing strong evidence of time-series momentum.[12] Nonetheless, not all coefficients are statistically significant. For a given look-back period, the magnitude of the coefficient and its statistical significance tend to increase and then decrease as the holding period increases. When the look-back period is longer, the most significant coefficient is observed at a shorter holding period. Similarly, for a given holding period, the coefficient tends to increase and then decrease, and the most significant value is found at a shorter look-back period when the holding period is longer. These results suggest that the price moves in the same direction for a certain period before it reverses. From the table, the trend appears to last for about 30 to 40 days. The coefficient has the highest t-statistic of 4.08 when $j = 28$ and $k = 1$. The coefficient loses statistical significance when both the look-back and holding periods extend beyond 28 days.

To test time-series momentum strategies in the next section, we choose look-back and holding period pairs whose coefficients are large and statistically significant. Based on this criterion, the look-back periods from 7 to 28 days and the holding periods from 1 to 14 days are selected for the portfolio analysis.

4.2 Portfolio analysis

4.2.1 Time-series momentum portfolios

To construct a time-series momentum strategy, we categorize the past returns of the market portfolio into terciles. When the look-back period return falls within the top third of the historical returns, the strategy takes a long position in the market portfolio. Conversely, if the return falls within the bottom third, it takes a short position in the market portfolio. Otherwise, it clears all positions and holds cash. Note that this strategy holds either a long position or a short position on a given date but not both and is different from the cross-sectional momentum strategy that holds positions on both sides at the same time. Table 5 reports the performance of the long-only, short-only, and long-short portfolios with different look-back and holding periods.

Remarkably, all long-only portfolios exhibit superior performance compared to the market portfolio in terms of the Sharpe ratio and the cumulative return. Even after accounting for the transaction costs, all long-only portfolios except for (7, 7) outperform the market. The superior perfor-

[12] We henceforth use the notation (j, k) to denote a pair of j-day look-back period and k-day holding period.

Table 4: Regression of time-series momentum

This table reports the results of the time-series momentum regression defined in Equation (14). The dependent variable is the time-series percentile rank of the holding period return, and the independent variable is the time-series percentile rank of the look-back period return. The figures are the estimates of β and Newey-West adjusted t-statistics.

	Holding period (k)										
Look-back (j)	1	3	5	7	14	21	28	35	42	49	56
1	-0.032	0.026	0.020	0.036	0.045	0.041	0.054	0.052	0.041	0.048	0.047
	(-1.79)	(1.43)	(1.06)	(1.93)	(2.29)	(1.93)	(2.63)	(2.46)	(1.93)	(2.23)	(2.25)
3	0.026	0.055	0.067	0.063	0.077	0.068	0.083	0.084	0.066	0.070	0.065
	(1.43)	(2.37)	(2.60)	(2.38)	(2.54)	(2.13)	(2.70)	(2.67)	(1.97)	(2.13)	(2.00)
5	0.023	0.068	0.070	0.069	0.092	0.075	0.096	0.090	0.075	0.079	0.070
	(1.26)	(2.67)	(2.51)	(2.31)	(2.54)	(1.95)	(2.57)	(2.36)	(1.84)	(1.96)	(1.72)
7	0.049	0.075	0.078	0.074	0.108	0.091	0.110	0.099	0.086	0.087	0.078
	(2.73)	(2.81)	(2.57)	(2.31)	(2.67)	(2.11)	(2.61)	(2.23)	(1.82)	(1.84)	(1.66)
14	0.061	0.099	0.107	0.117	0.127	0.132	0.134	0.119	0.103	0.100	0.091
	(3.21)	(3.33)	(3.01)	(3.02)	(2.76)	(2.71)	(2.57)	(2.08)	(1.68)	(1.6)	(1.45)
21	0.065	0.089	0.092	0.102	0.126	0.123	0.124	0.109	0.095	0.090	0.090
	(3.45)	(3.04)	(2.63)	(2.71)	(2.69)	(2.40)	(2.15)	(1.67)	(1.36)	(1.27)	(1.27)
28	0.075	0.101	0.105	0.120	0.134	0.132	0.127	0.111	0.099	0.100	0.108
	(4.08)	(3.57)	(3.20)	(3.28)	(2.69)	(2.30)	(2.00)	(1.54)	(1.32)	(1.31)	(1.42)
35	0.074	0.101	0.102	0.112	0.125	0.119	0.117	0.103	0.098	0.106	0.116
	(3.83)	(3.33)	(2.82)	(2.71)	(2.23)	(1.88)	(1.65)	(1.38)	(1.25)	(1.35)	(1.47)
42	0.069	0.091	0.084	0.091	0.103	0.097	0.095	0.097	0.100	0.107	0.116
	(3.38)	(2.80)	(2.13)	(2.03)	(1.73)	(1.43)	(1.26)	(1.23)	(1.27)	(1.35)	(1.45)
49	0.065	0.083	0.077	0.086	0.092	0.082	0.092	0.106	0.108	0.111	0.124
	(2.95)	(2.43)	(1.87)	(1.83)	(1.49)	(1.14)	(1.19)	(1.32)	(1.34)	(1.39)	(1.53)
56	0.067	0.084	0.073	0.079	0.085	0.091	0.111	0.125	0.130	0.140	0.150
	(3.06)	(2.37)	(1.68)	(1.63)	(1.36)	(1.28)	(1.43)	(1.55)	(1.60)	(1.72)	(1.83)

mance mainly results from the reduced risk as evidenced by the low standard deviations and MDDs compared to those of the market. The (28, 5) portfolio yields the highest Sharpe ratio of 1.51 and a cumulative return of 36,686%, which are significantly higher than those of the market, 0.85 and 2,696%. It holds a position for 48% of the sample period. The portfolios with a look-back period of 28 days always outperform the others with the same holding period. Transaction costs impact the performance more when the holding period is shorter due to more frequent rebalancing. Still, the impact is not severe since the strategy takes positions only when the momentum condition is met.

Contrary to the long-only portfolios, the short-only portfolios yield unfavorable outcomes. All the portfolios but (21, 7) make losses at the end of the sample period even without transaction costs. It appears that time-series momentum is almost non-existent when the market is bearish. Consequently, the long-short portfolios underperform their long-only counterparts. Adding short positions only erodes the mean return without reducing the risk.

Since short positions do not add value to the strategies, we focus on the best-performing long-only portfolio, (28, 5), for detailed analysis below. Figure 4 displays the log-scale cumulative returns of the (28, 5) portfolio and the market. The strategy defends well against market downturns. With its nature of buying the market only when the market is in an upward trend, it underperforms the market when the market goes up, but it successfully times a bearish market and avoids large drawdowns. The year-by-year performance reported in Table IA3 confirms that the superior performance of the (28, 5) strategy is not due to a few lucky years. It has a higher Sharpe ratio than the market in eight of the ten years and a lower standard deviation and MDD in all years.

Overall, the results suggest that there is a serial correlation in the cryptocurrency market and a time-series momentum strategy with carefully chosen look-back and holding periods can earn significant profits. Nevertheless, as a naked strategy, it is exposed to the high risk of the cryptocurrency market and can generate profits in the future only if the market continues to grow.

4.2.2 Factor regression

Liu et al. (2022) propose a three-factor cryptocurrency model, which consists of market, size, and momentum factors. This section tests whether these factors can explain the time-series momentum premium. We construct the factors following Liu et al. (2022), as summarized below. The market factor is defined as the excess return of the value-weighted market portfolio. The three-month U.S. treasury bill rate is used as a proxy for the risk-free rate. For the size factor, coins are split into

Table 5: Performance of time-series momentum portfolios

This table reports the performance of time-series momentum portfolios of various look-back and holding periods, $(j,\ k)$. 'L', 'S', and 'LS' respectively denote the long-only, short-only, and long-short portfolios, and 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively represent the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 26, 2014, to August 28, 2023. A transaction cost of 15 bps is assumed.

	L					S					LS				
(j,k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(7, 1)	58.86	43.70	1.35	11697.4	52.0	-12.23	47.85	-0.26	-89.8	92.8	48.75	64.73	0.75	1390.5	66.6
(7, 3)	59.08	48.22	1.23	9743.9	61.0	-5.80	50.97	-0.11	-83.5	91.8	60.76	68.38	0.89	3678.0	67.0
(7, 5)	55.63	52.76	1.05	5389.3	74.8	-13.47	54.49	-0.25	-93.5	96.4	35.95	70.19	0.51	187.8	92.3
(7, 7)	50.22	54.74	0.92	2817.0	79.4	-9.61	53.69	-0.18	-90.1	94.6	30.28	70.11	0.43	67.4	88.2
(7, 14)	69.81	60.79	1.15	13773.1	79.0	-27.62	61.05	-0.45	-98.8	99.5	58.24	72.76	0.80	2008.6	93.9
(14, 1)	57.50	45.46	1.26	9392.0	52.4	0.22	48.75	0.00	-67.2	79.6	58.69	66.39	0.88	3374.2	51.3
(14, 3)	61.41	47.96	1.28	12262.2	53.4	-1.88	49.33	-0.04	-74.0	83.5	61.36	67.90	0.90	3996.6	66.2
(14, 5)	64.81	49.34	1.31	16007.0	56.2	-0.61	50.05	-0.01	-72.0	82.4	66.76	68.28	0.98	6584.3	59.0
(14, 7)	67.36	50.58	1.33	19278.7	55.5	-7.30	52.27	-0.14	-86.8	93.3	73.33	69.01	1.06	12005.5	68.1
(14, 14)	53.33	56.20	0.95	3609.5	72.6	-3.61	54.20	-0.07	-82.6	92.3	32.08	71.29	0.45	85.5	95.6
(21, 1)	59.85	45.26	1.32	11923.4	58.5	2.60	48.10	0.05	-57.7	79.4	62.66	65.43	0.96	5286.5	58.9
(21, 3)	59.72	47.76	1.25	10521.6	59.0	5.44	48.72	0.11	-45.9	76.8	66.81	67.26	0.99	7078.9	63.6
(21, 5)	49.70	49.51	1.00	3571.2	67.0	10.14	49.48	0.20	-17.6	69.9	51.50	68.27	0.75	1410.7	77.8
(21, 7)	50.90	51.52	0.99	3642.7	70.2	12.99	49.06	0.26	10.0	70.1	52.25	69.10	0.76	1428.5	81.4
(21, 14)	58.86	54.70	1.08	6728.0	76.6	-4.52	53.57	-0.08	-83.9	94.4	63.87	71.04	0.90	4024.5	87.7
(28, 1)	69.16	44.99	1.54	29842.2	62.7	-4.42	47.16	-0.09	-77.7	87.5	65.12	64.69	1.01	7025.3	61.0
(28, 3)	68.38	47.14	1.45	25139.9	61.1	-0.56	47.65	-0.01	-68.3	84.6	67.45	66.13	1.02	8077.2	63.8
(28, 5)	75.37	48.34	1.56	46787.0	61.0	0.18	48.44	0.00	-67.4	86.5	77.15	67.23	1.15	19167.2	59.2
(28, 7)	73.96	48.26	1.53	40961.4	61.6	2.22	48.90	0.05	-60.9	79.1	77.74	67.49	1.15	20045.6	61.9
(28, 14)	66.30	54.09	1.23	14431.1	71.3	4.24	52.64	0.08	-60.0	86.7	68.10	70.09	0.97	6613.6	81.8

(a) Performance before transaction costs

	L					S					LS				
(j,k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(7, 1)	50.39	43.73	1.15	5096.1	56.2	-20.66	47.89	-0.43	-95.5	96.7	31.88	64.80	0.49	190.2	80.9
(7, 3)	52.51	48.27	1.09	5108.0	63.2	-12.01	51.01	-0.24	-91.0	95.3	48.89	68.46	0.71	1092.7	73.3
(7, 5)	50.22	52.81	0.95	3144.8	77.6	-19.07	54.54	-0.35	-96.2	97.6	26.08	70.29	0.37	9.9	94.5
(7, 7)	45.12	54.81	0.82	1675.0	81.7	-14.85	53.78	-0.28	-94.0	96.7	21.61	70.28	0.31	-28.5	91.6
(7, 14)	66.56	60.86	1.09	9989.0	79.9	-31.31	61.19	-0.51	-99.2	99.6	53.65	72.86	0.74	1241.0	94.3
(14, 1)	51.98	45.48	1.14	5463.8	54.1	-5.25	48.77	-0.11	-80.7	86.9	47.73	66.43	0.72	1100.3	60.4
(14, 3)	57.12	47.98	1.19	8065.2	54.9	-6.09	49.36	-0.12	-82.7	88.3	53.12	67.97	0.78	1738.3	71.5
(14, 5)	60.98	49.36	1.24	11009.8	58.2	-4.49	50.09	-0.09	-80.8	86.9	59.66	68.34	0.87	3252.3	61.0
(14, 7)	64.11	50.62	1.27	14025.6	56.6	-10.60	52.34	-0.20	-90.4	95.0	67.35	69.10	0.97	6654.9	72.6
(14, 14)	50.61	56.25	0.90	2742.5	73.3	-1.96	30.90	-0.06	-47.5	74.3	27.50	71.44	0.38	17.8	96.2
(21, 1)	54.90	45.28	1.21	7343.6	60.4	-2.61	48.11	-0.05	-74.5	85.3	52.49	65.46	0.80	1911.2	63.7
(21, 3)	56.23	47.78	1.18	7470.8	60.1	1.78	48.74	0.04	-62.1	81.6	59.83	67.31	0.89	3546.5	65.4
(21, 5)	46.72	49.54	0.94	2648.3	69.0	7.10	49.53	0.14	-38.8	73.6	45.97	68.36	0.67	779.4	80.4
(21, 7)	48.13	51.57	0.93	2756.5	71.8	10.37	49.10	0.21	-14.8	73.8	47.29	69.18	0.68	840.7	81.8
(21, 14)	56.84	54.75	1.04	5504.3	77.7	-6.82	53.62	-0.13	-87.2	95.2	60.24	71.10	0.85	2790.4	88.9
(28, 1)	65.04	45.00	1.45	19991.6	63.5	-8.78	47.19	-0.19	-85.4	90.9	56.63	64.72	0.88	3031.6	64.5
(28, 3)	65.39	47.17	1.39	18782.8	61.9	-3.66	47.68	-0.08	-76.6	87.7	61.40	66.19	0.93	4438.9	65.0
(28, 5)	72.85	48.34	1.51	36685.8	61.8	-2.44	48.49	-0.05	-74.8	88.9	72.17	67.27	1.07	11780.6	60.2
(28, 7)	71.71	48.28	1.49	32921.4	62.4	-0.02	48.95	0.00	-68.6	82.1	73.50	67.55	1.09	13227.4	62.4
(28, 14)	64.60	54.12	1.19	12206.5	71.9	2.36	52.66	0.04	-66.7	87.6	64.88	70.16	0.92	4790.0	82.6
Market											62.37	73.63	0.85	2695.9	89.1

(b) Performance after transaction costs

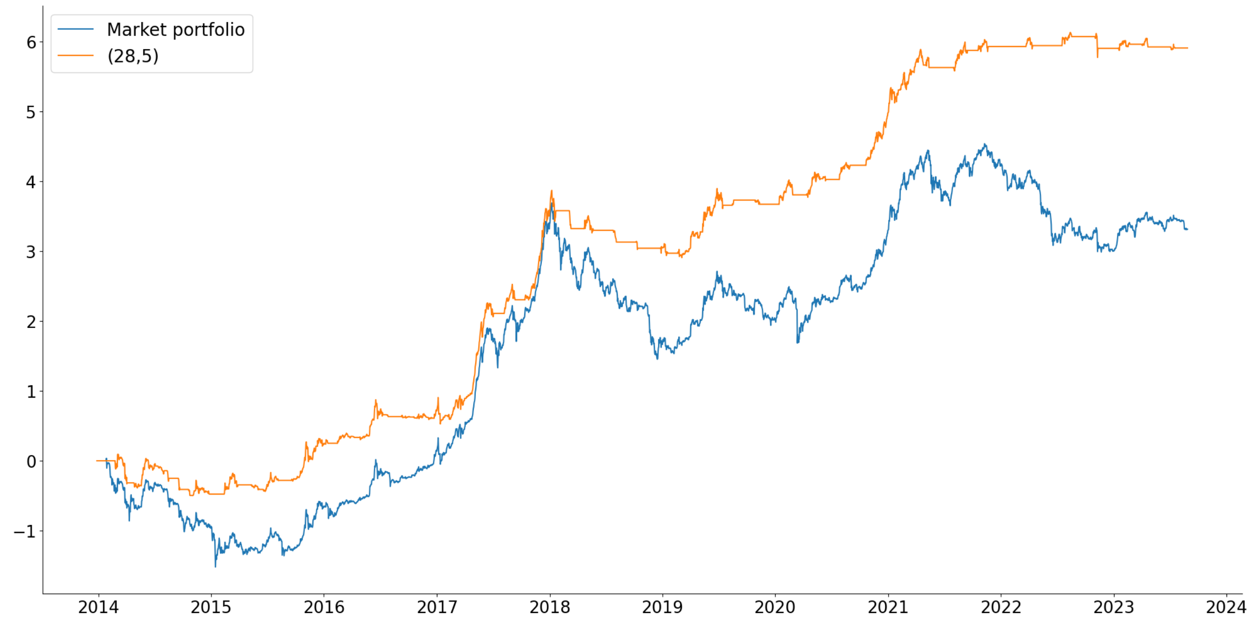


Figure 4: Time-series momentum portfolio log-scale cumulative returns

three groups on market capitalization; Small (bottom 30%), Middle (middle 40%), and Big (top 30%), and a value-weighted portfolio is formed within each size group. The size factor is the return of the Small-minus-Big portfolio. For the momentum factor, coins are split into two size groups and further split into three momentum groups within each size group; Low (bottom 30%), Middle (middle 40%), and High (top 30%), based on the past three-week return. The momentum factor portfolio is constructed as

$$MOM = 1/2(Small\ High + Big\ High) - 1/2(Small\ Low + Big\ Low). \tag{15}$$

In addition to the three factors, we also consider two factors related to overreaction. Byun et al. (2016), based on the model of Daniel et al. (1998), develop a measure of continuing overreaction that captures both the magnitude and direction of overreaction, which is defined as

$$CO_{i,t} = \frac{\sum_{j=1}^{J}(J-j+1)\cdot sign(r_{i,t-j})\cdot Vol_{i,t-j}}{\sum_{j=1}^{J} Vol_{i,t-j}/J}, \tag{16}$$

where $sign(r_{i,t})$ is the sign of the return of coin i on day t and $Vol_{i,t}$ is the trading volume. $CO_{i,t}$ has a positive (negative) value if the trading volume is high when the return is positive (negative).

We construct two overreaction factors using the continuing overreaction measure, a cross-sectional overreaction factor (CS-CO) and a time-series overreaction factor (TS-CO). For the cross-sectional overreaction factor, we follow the method for the momentum factor, *i.e.*, split coins into two size groups and further into three groups based on the continuing overreaction measure, and form a long-short portfolio that goes long on high CO coins and short on low CO coins. For the time-series overreaction factor, we calculate the CO of the market portfolio and make a factor portfolio that goes long on the market portfolio when its CO measure is positive. The TS-CO factor portfolio is designed to take only long positions as the time-series momentum portfolio takes only long positions. For both CS-CO and TS-CO factors, J is set to three weeks following the momentum factor.

Table 6 reports the factor regression results of the (28, 5) long-only portfolio. When the portfolio returns are regressed on a single factor, the time-series overreaction factor turns out to be the most important factor with a t-statistic of 6.52. The TS-CO factor also has the most explanatory power (adj $R^2 = 0.088$) and is the only factor that renders an insignificant alpha. The other significant factors are the market factor (t-statistic = 5.43) and the CS-CO factor (t-statistic = 2.38). The size and momentum factors are insignificant. Regression (7) shows that Liu et al. (2022) three-factor model cannot explain the return of the time-series momentum portfolio: The t-statistic of the alpha is 3.28. When the return is regressed on all five factors (regression (9)), the TS-CO factor remains the only significant factor and the alpha becomes insignificant.

The explanatory power of the TS-CO factor suggests that overreaction is the main driver of time-series momentum. Daniel et al. (1998) theoretically show that overreaction induced by self-attribution and overconfidence of investors can result in momentum. Byun et al. (2016) and Adebambo and Yan (2016) provide supporting evidence. The cryptocurrency market is considered a playground for retail investors and hidden speculators. Only a tiny portion of Bitcoin and Ethereum, 1.23% and 0.03%, respectively, are in public companies' hands.[13] As retail investors are known to be more overconfident than institutional investors, the dominance of retail investors in the cryptocurrency market is a plausible cause of time-series momentum.

4.2.3 Market dependency of time-series momentum

Prior studies find that time-series momentum depends on market conditions. Moskowitz et al. (2012) reveal that a time-series momentum portfolio is more profitable when the market is volatile. Lim et al. (2018) observe that time-series momentum performs exceptionally well during an extreme bear market, but exhibits weak performance during an extreme bull market. On the contrary,

[13] `https://www.coingecko.com/en/public-companies-bitcoin`.

Table 6: Time-series momentum portfolio factor regression

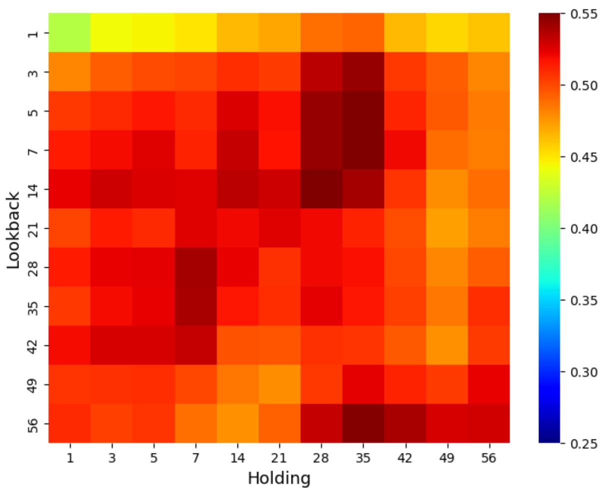
This table reports the factor regression results of the (28, 5) time-series momentum long-only portfolio. The factors are market (MKT), size (SIZE), momentum (MOM), cross-sectional continuing overreaction (CS-CO), and time-series continuing overreaction (TS-CO). The definitions of the factors can be found in Section 4.2.2. The sample period is from January 26, 2014 to August 28, 2023. The t-statistics are Newey-West adjusted t-statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	0.0024	0.0029	0.0029	0.0028	0.0010	0.0024	0.0024	0.0024	0.0012
	(3.34)	(3.64)	(3.59)	(3.53)	(1.38)	(3.34)	(3.28)	(3.26)	(1.48)
MKT	0.0606					0.0615	0.0615	0.0604	0.0163
	(5.43)					(5.37)	(5.38)	(5.36)	(1.24)
SIZE		-0.0010				-0.0078	-0.0083	-0.0094	-0.0063
		(-0.08)				(-0.70)	(-0.74)	(-0.77)	(-0.53)
MOM			0.0019				0.0017	0.0010	-0.0028
			(0.33)				(0.33)	(0.22)	(-0.58)
CS-CO				0.0215				0.0050	0.0021
				(2.38)				(0.48)	(0.20)
TS-CO					0.1180				0.1009
					(6.52)				(4.06)
Adj R^2	0.057	0.000	0.000	0.005	0.088	0.057	0.057	0.057	0.090

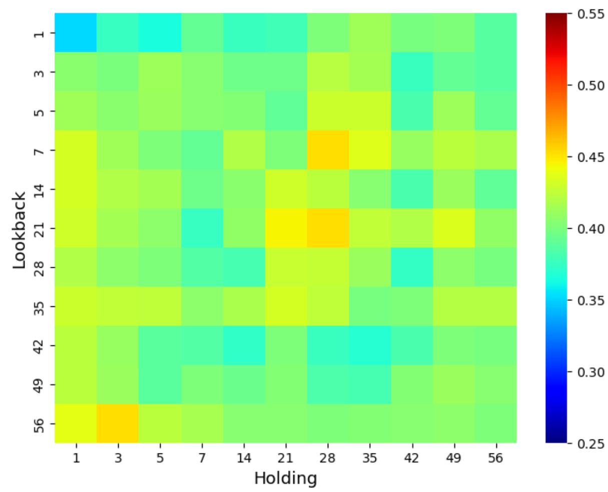
Liu and Tsyvinski (2021) find that cryptocurrency time-series momentum is stronger when the market is bullish. The portfolio performance in the previous section also suggests that a time-series momentum strategy performs better in a bullish market.

To examine time-series momentum's market dependency more in detail, we divide look-back and holding period returns into quintiles (Q1 to Q5 in ascending order) and calculate transition probabilities between them. Figure 5 presents the results using heatmaps. In the figure, panel (a) displays the transition probability from Q5 to Q4 or Q5, $P(\mathrm{Q5} \to \mathrm{Q4}, \mathrm{Q5})$, and similarly, panels (b), (c), and (d) display $P(\mathrm{Q1} \to \mathrm{Q1}, \mathrm{Q2})$, $P(\mathrm{Q5} \to \mathrm{Q1}, \mathrm{Q2})$, and $P(\mathrm{Q1} \to \mathrm{Q4}, \mathrm{Q5})$, respectively. If momentum prevails, we would observe higher probabilities in panels (a) and (b), whereas if reversal prevails, we would observe higher probabilities in panels (c) and (d). If the transition occurs randomly, $P(\mathrm{Q}_i \to \mathrm{Q}_j, \mathrm{Q}_k)$ would be 40% for all i, j, and k.

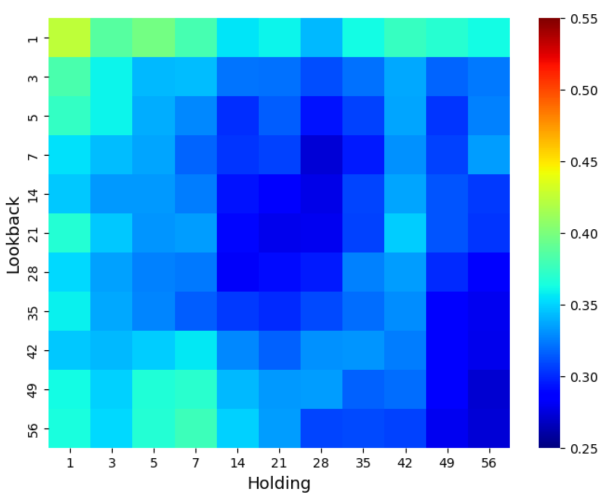
The probability $P(\mathrm{Q5} \to \mathrm{Q4}, \mathrm{Q5})$ is higher than 40%, whereas $P(\mathrm{Q5} \to \mathrm{Q1}, \mathrm{Q2})$ is lower than 40% for most periods, which suggests a strong time-series momentum effect in a bullish market. The momentum effect is particularly strong when the look-back period is between 7 to 28 days and the holding period between 14 to 28 days. In contrast, when the look-back period return is in the lowest quintile (Q1), we cannot observe a momentum effect: We rather observe a weak reversal effect in some periods. For the (28, 5) strategy, $P(\mathrm{Q5} \to \mathrm{Q4}, \mathrm{Q5})$ is 52.32% and $P(\mathrm{Q5} \to \mathrm{Q1}, \mathrm{Q2})$ is 32.52%, whereas $P(\mathrm{Q1} \to \mathrm{Q1}, \mathrm{Q2})$ is 40.03% and $P(\mathrm{Q1} \to \mathrm{Q4}, \mathrm{Q5})$ is 46.49%. This result is consistent with the findings of Liu and Tsyvinski (2021).



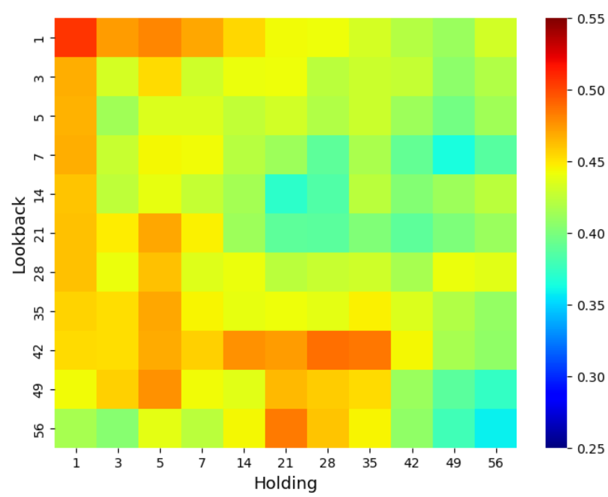
(a) Q5 → Q4,Q5



(b) Q1 → Q1,Q2



(c) Q5 → Q1,Q2



(d) Q1 → Q4,Q5

Figure 5: Transition probabilities between look-back and holding period returns of the market portfolio

As a robustness check, we run the regression at different market states. We define the market state as good, normal, or bad if the look-back period return is in the top third, middle third, or bottom third, and run the percentile rank regression in each market state. Table IA4 reports the results in good and bad states. The results show that when the market is in a good state, the coefficient is significant for the majority of the look-back and holding periods and its t-statistic is higher than the corresponding t-statistic in Table 4. On the other hand, when the market is in a bad state, the coefficient is always insignificant. This result reaffirms that time-series momentum is more pronounced when the market is bullish.

4.2.4 Double sorting

This section examines whether time-series momentum is concentrated in a specific coin type. We split coins into different size, volume, and overreaction groups, and compare the effect of time-series momentum across the groups using the (28, 5) long-only strategy. Since there are only a handful of coins before 2017, we use the sample from the beginning of 2017. Table 7 reports the results.

Remarkably, the time-series momentum strategy outperforms the buy-and-hold strategy in all groups but CO2. It earns a higher Sharpe ratio and has a lower MDD than the buy-and-hold strategy. As to the performance variation across the groups, it performs comparably across the size and volume groups. The variation is more noticeable across the overreaction groups, but no distinct pattern can be observed. Coins are highly correlated: Due to the lack of fundamentals, they tend to move in tandem following the movement of Bitcoin. As the performance of a time-series momentum strategy is determined by the aggregate performance of the coins in the portfolio, not by their relative performance, it does not vary significantly across different types of coins.

4.2.5 Summary of findings and discussion

The regression and portfolio analyses suggest that time-series momentum is widespread across diverse look-back and holding periods when the market is trending upward. The trend lasts about 30 to 40 days. In contrast, the momentum effect is not observable when the market is bearish and the long-short portfolio underperforms the long-only portfolio of the same look-back and holding periods. The double-sorting results show that time-series momentum works consistently across different size, volume, and overreaction groups.

Liu and Tsyvinski (2021) attribute the time-series momentum effect to underreaction, based on the observation that low-attention (measured by Google attention data) coins exhibit stronger time-

Table 7: Performance of time-series momentum in different coin groups

This table reports the performance of the (28, 5) time-series momentum long-only portfolio in different coin groups. Coins are grouped on size (panel (a)), trading volume (panel (b)), or continuing overreaction (panel (c)), and a buy-and-hold portfolio and a (28, 5) long-only portfolio are formed within each group. Coins are value-weighted when grouped on size or continuing overreaction, and volume-weighted when grouped on volume. 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 1, 2017, to August 28, 2023. A transaction cost of 15 bps is assumed.

	Buy-and-hold					Time-series momentum				
Group	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
M1	86.89	105.49	0.82	784.8	98.2	129.45	79.38	1.63	73197.2	73.7
M2	93.87	99.69	0.94	1732.6	97.8	125.58	74.30	1.69	68499.6	77.0
M3	75.30	98.64	0.76	563.7	98.3	104.47	67.26	1.55	23239.9	78.5
M4	101.91	108.95	0.94	2039.0	96.8	147.20	90.67	1.62	166677.5	77.0
M5	77.68	77.56	1.00	2278.6	88.9	80.00	49.53	1.62	8988.9	61.6
Market						78.86	77.80	1.01	2333.3	89.1

(a) Double sorting on size and momentum

	Buy-and-hold					Time-series momentum				
Group	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
V1	110.54	92.63	1.19	8449.4	92.9	115.79	65.85	1.76	52432.9	73.1
V2	124.52	102.66	1.21	12497.7	96.3	131.44	80.33	1.64	80204.6	85.6
V3	104.64	102.23	1.02	3116.3	99.3	128.25	69.31	1.85	107193.8	64.9
V4	63.08	106.23	0.59	156.8	98.9	128.46	89.33	1.44	47426.4	70.7
V5	68.23	83.59	0.82	869.4	92.1	88.81	53.15	1.67	14256.6	71.2
Market						78.86	77.80	1.01	2333.3	89.1

(b) Double sorting on volume and momentum

	Buy-and-hold					Time-series momentum				
Group	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
CO1	48.66	87.02	0.56	198.6	95.6	73.35	58.90	1.25	4127.6	70.1
CO2	91.00	94.03	0.97	2259.9	91.2	44.84	66.76	0.67	452.7	80.8
CO3	103.34	97.53	1.06	4147.1	92.8	112.75	79.04	1.43	23389.6	73.4
CO4	107.76	101.75	1.06	4285.4	96.4	122.43	73.80	1.66	57133.2	72.1
CO5	76.58	86.67	0.88	1265.1	91.8	67.59	51.11	1.32	3747.2	57.9
Market						78.86	77.80	1.01	2333.3	89.1

(c) Double sorting on continuing overreaction and momentum series momentum. Our findings, however, do not support their argument. When we split coins into different volume (a proxy for attention) groups and form a time-series momentum portfolio within each group, they perform comparably. The portfolio in the lowest volume group yields a slightly higher Sharpe ratio than the highest volume group portfolio, but the difference is trivial (1.76 vs. 1.67). The empirical fact that the TS-CO factor can explain the momentum premium rather supports an overreaction mechanism. Our results are different from those of Liu and Tsyvinski (2021) possibly because they use only ten major coins and a different sample period.

4.3 Further analysis

This section conducts various analyses to better understand time-series momentum in the cryptocurrency market and to check the robustness of earlier findings. All the results presented in this section are for the (28, 5) long-only strategy and take transaction costs into account unless otherwise noted.

4.3.1 Different weighting schemes

This section tests the robustness of time-series momentum across different portfolio weighting schemes. Specifically, we test time-series momentum using capped-value-weighted, volume-weighted, capped-volume-weighted, and equal-weighted portfolios. Table 8 compares the performance of the (28, 5) long-only strategy with the buy-and-hold strategy under each weighting scheme.

The time-series momentum strategy outperforms the buy-and-hold strategy regardless of the portfolio formation method. It has a higher Sharpe ratio and cumulative return, and a lower MDD than the buy-and-hold strategy in all cases. The capped-value-weighted portfolio yields the highest Sharpe ratio of 1.65, but the variation of the performance across the weighting schemes is small. The lowest Sharpe ratio obtained from the capped-volume-weighted portfolio is still 1.40. This result is consistent with the double-sorting result.

4.3.2 Different entry thresholds

This section tests the robustness of time-series momentum across different entry thresholds, *i.e.*, when to enter the market. If higher look-back period returns are associated with higher holding period returns, a stricter threshold would lead to higher returns when the strategy buys the market. However, a stricter threshold also means fewer trading opportunities. With these two offsetting effects, it is unclear how the threshold will affect the portfolio performance. Table 9 reports the

Table 8: Performance of time-series momentum under different weighting schemes

This table reports the performance of the (28, 5) time-series momentum long-only portfolio under different weighting schemes: value-weight (Value), volume-weight (Volume), capped-value-weight (CapValue), capped-volume-weight (CapVolume), and equal-weight (Equal). 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 26, 2014, to August 28, 2023. A transaction cost of 15 bps is assumed.

	Buy-and-hold					Time-series momentum				
Scheme	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
Value	61.48	73.55	0.84	2481.4	89.2	72.85	48.34	1.51	36783.0	61.8
CapValue	61.89	80.99	0.76	1506.3	94.3	86.02	52.28	1.65	107977.8	53.5
Volume	57.74	78.96	0.73	1197.3	92.4	74.01	50.65	1.46	36688.5	68.5
CapVolume	42.82	86.36	0.50	154.4	98.1	79.27	56.45	1.40	45158.7	61.3
Equal	74.54	88.26	0.84	2782.4	97.1	94.17	60.78	1.55	149367.6	75.6

results, in which the first column represents the entry threshold, *e.g.*, 10% means the strategy enters a long position on the market if the look-back period return is within the top 10% of the historical returns.

The performance during the periods when the portfolio holds a position shows that the performance improves until the threshold reaches 10% and then drops thereafter. When the threshold is higher than 10%, the mean return decreases while the standard deviation increases, which implies that if the market appreciates exceptionally, the trend is more likely to become weaker or reversed. While the threshold of 10% renders the best performance during the holding period, the overall performance over the sample period is found to be better at a lower threshold owing to more frequent trading. An optimal trade-off between profitability and trading opportunity appears to occur when the threshold is between 30% and 50%.

Table 9: Performance of time-series momentum under different entry thresholds

This table reports the performance of the (28, 5) time-series momentum long-only portfolio under different entry thresholds. The x% in the first column means the strategy buys the market if the look-back period return is within the top x% of the historical returns. The results under 'Sample period' are the performance over the entire sample period and those under 'Holding period' are the performance during the periods of position holding. 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 26, 2014, to August 28, 2023. A transaction cost of 15 bps is assumed.

	Sample period					Holding period			Entry	
	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Count	Ratio
50%	74.52	54.51	1.37	31505.4	68.5	120.86	69.34	1.74	435	61.58%
40%	69.32	51.81	1.34	21959.9	59.6	129.54	70.68	1.83	378	53.51%
30%	62.38	45.73	1.36	15036.7	65.2	142.62	68.93	2.07	309	43.74%
20%	51.56	42.46	1.21	6072.9	51.4	150.53	72.28	2.08	242	34.26%
10%	33.59	35.63	0.94	1391.5	40.8	172.91	80.85	2.14	136	19.25%
5%	16.36	29.01	0.56	323.3	48.1	158.13	91.20	1.73	71	10.05%
1%	10.54	22.81	0.46	215.3	40.8	156.71	90.83	1.73	44	6.23%

4.3.3 Day-of-the-week effect

This section examines the performance variation when the entire wealth is invested on a specific day of the week. Table 10 reports the results of the (28, 7) long-only portfolio, where rows represent the rebalancing day.[14]

The impact of the rebalancing day is nontrivial. The portfolio investing on Mondays yields the highest Sharpe ratio of 1.40, whereas the portfolio investing on Sundays yields the lowest Sharpe ratio of 1.09. The difference mainly results from the mean return. Figure 6 displays the log-scale cumulative returns of the best and the worst cases. Interestingly, the portfolio rebalancing on Sundays performs poorly, especially when the market is bearish. This result demonstrates how an empirical study can be distorted when it assumes rebalancing on a particular day of the week.

Table 10: Performance of time-series momentum under different rebalancing days

This table reports the performance of the (28, 7) time-series momentum long-only portfolio under different rebalancing days. 'Distributed' means investing evenly throughout the week. 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 26, 2014, to August 28, 2023. A transaction cost of 15 bps is assumed.

	Mean	Std	Sharpe	Cum	MDD
Mon	62.75	44.79	1.40	16223.0	65.2
Tue	52.48	44.35	1.18	6120.5	71.9
Wed	57.19	44.85	1.28	9418.5	50.3
Thu	57.49	45.43	1.27	9448.7	52.9
Fri	57.71	45.58	1.27	9617.9	49.5
Sat	61.19	45.93	1.33	13259.7	59.2
Sun	49.91	45.87	1.09	4465.1	68.4
Distributed	56.96	42.91	1.33	10027.6	58.7

4.3.4 Individual coin time-series momentum

This section examines whether a long-short portfolio based on the time-series momentum of individual coins can generate profits. We consider two long-short strategies. In the first strategy, the long (short) leg consists of the coins whose look-back period return is in the top (bottom) 20% of their historical returns. Thus, the number of coins in the long leg is usually different from the number of coins in the short leg. For the second strategy, we sort the coins on their time-series percentile rank of the look-back period return and form a long-short portfolio by buying the coins in the top 20% and shorting those in the bottom 20%. Thus, both legs have the same number of

[14] We use a holding period of seven days instead of five to compare the impacts of all seven days of the week.

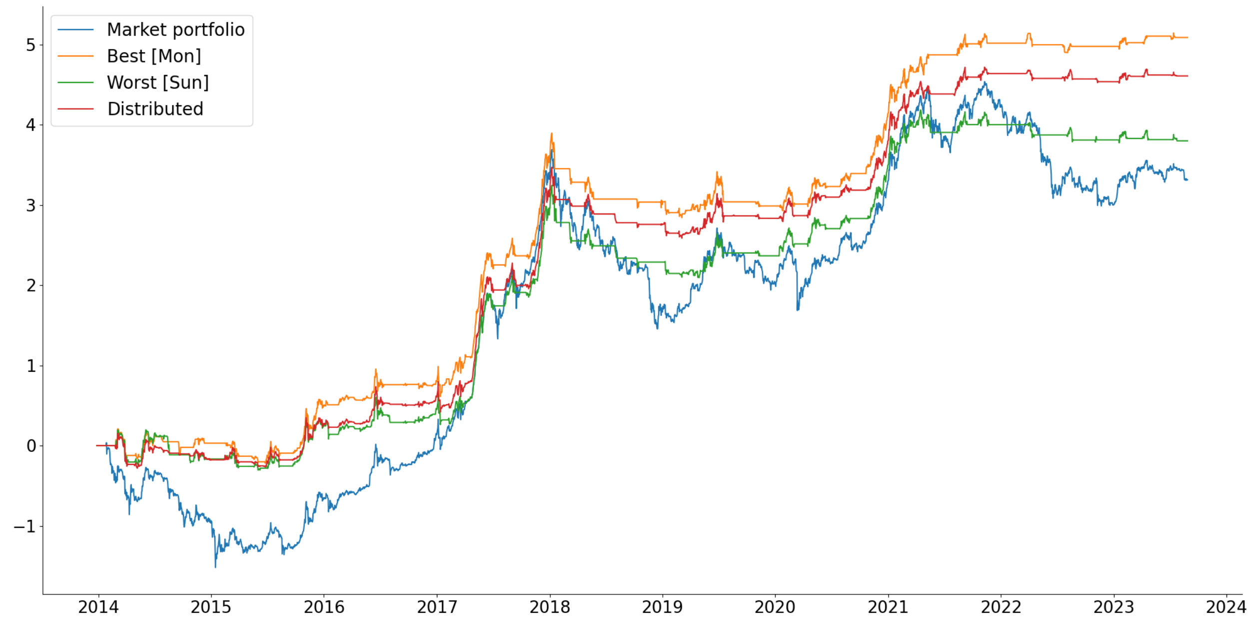


Figure 6: The (28, 7) time-series momentum portfolio cumulative returns under different rebalancing days

coins in this strategy. Table 11 reports the performance of these strategies.[15]

Neither of the strategies are impressive. They earn a negative profit for the majority of the look-back and holding periods. Only one portfolio of the first strategy, (7, 5), and one of the second strategy, (7, 7), marginally outperform the market in terms of the Sharpe ratio. A cross-sectional comparison of time-series momentum does not appear to work. The better performing portfolios have a look-back period of seven days and a holding period of five or seven days in both strategies. Recall that the time-series momentum strategy that buys the market performs best when the look-back and holding periods are twenty-four and five days, respectively. The time-series momentum of the market is predominantly determined by Bitcoin and other major coins. The fact that the time-series momentum at the individual coin level performs best at a shorter look-back period implies that minor coins reverse more quickly than major ones.

5 Cross-sectional momentum

In this section, we test cross-sectional momentum in the cryptocurrency market. As before, we first carry out a regression analysis to identify look-back and holding period pairs that are likely to render profitable momentum strategies and conduct a comprehensive analysis of those strategies.

[15]The pooled regression result of individual coins' time-series moment is reported in Table IA6.

Table 11: Performance of time-series momentum long-short portfolios

This table reports the performance of the long-short portfolios formed on the time-series momentum of individual coins. Two long-short strategies are considered. In the first strategy (panel (a)), the long (short) leg consists of the coins whose look-back period return is in the top (bottom) 20% of their historical returns. In the second strategy (panel (b)), coins are sorted on their time-series percentile rank of the look-back period return and a long-short portfolio is formed by buying the coins in the top 20% and shorting those in the bottom 20%.

	L					S					LS				
(j, k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(7, 1)	42.61	129.40	0.33	-91.6	99.9	-31.86	110.99	-0.29	-99.9	99.9	-5.66	136.86	-0.04	-99.9	100.0
(7, 3)	55.77	110.83	0.50	-30.3	99.5	50.58	103.27	0.49	-23.5	92.2	97.27	125.02	0.78	280.9	92.4
(7, 5)	80.76	106.03	0.76	430.5	92.6	41.02	91.55	0.45	-7.1	92.9	112.23	100.27	1.12	6237.1	68.4
(7, 7)	63.08	108.84	0.58	53.8	97.1	45.40	95.56	0.48	-7.9	95.6	117.45	115.91	1.01	3781.7	82.6
(7, 14)	89.28	111.74	0.80	698.0	94.5	-54.64	146.17	-0.37	-100.0	100.0	27.29	103.18	0.26	-81.9	95.6
(14, 1)	8.35	118.08	0.07	-98.6	99.8	-26.31	118.08	-0.22	-100.0	100.0	-37.43	131.93	-0.28	-100.0	100.0
(14, 3)	61.89	114.30	0.54	-22.3	96.3	37.03	101.87	0.36	-73.1	92.7	48.68	118.50	0.41	-87.1	97.0
(14, 5)	71.71	107.34	0.67	159.0	96.0	50.05	104.01	0.48	-75.1	97.4	76.99	107.18	0.72	167.2	85.1
(14, 7)	54.05	103.39	0.52	4.6	97.0	70.38	90.68	0.78	582.7	89.3	96.29	96.90	0.99	2410.0	79.4
(14, 14)	52.29	103.43	0.51	-5.7	97.7	32.85	87.69	0.37	-34.5	95.0	34.35	84.98	0.40	-9.8	89.8
(21, 1)	53.87	114.02	0.47	-53.7	99.2	-13.91	104.54	-0.13	-99.2	99.7	4.21	113.08	0.04	-98.5	99.8
(21, 3)	60.21	106.88	0.56	20.3	98.3	34.35	97.52	0.35	-61.2	96.1	55.80	95.16	0.59	97.5	93.7
(21, 5)	53.03	104.33	0.51	-8.4	98.2	45.38	95.69	0.47	-9.8	95.0	60.78	94.17	0.65	180.4	89.6
(21, 7)	52.24	103.51	0.50	-8.2	98.2	48.42	88.95	0.54	74.2	86.7	67.07	89.88	0.75	530.3	60.8
(21, 14)	34.95	94.54	0.37	-49.8	98.6	23.67	109.15	0.22	-93.2	99.3	5.90	85.34	0.07	-89.0	98.2
(28, 1)	30.04	110.10	0.27	-87.8	99.5	-26.59	111.99	-0.24	-99.8	100.0	-30.56	113.01	-0.27	-99.8	99.9
(28, 3)	36.70	104.36	0.35	-69.2	98.7	8.19	98.14	0.08	-93.7	99.5	6.70	96.15	0.07	-92.6	98.0
(28, 5)	36.41	104.40	0.35	-68.0	98.6	23.74	94.03	0.25	-76.6	98.2	24.39	95.46	0.26	-71.8	96.0
(28, 7)	44.96	103.94	0.43	-41.5	98.3	29.17	93.99	0.31	-66.4	93.4	36.92	92.37	0.40	-19.7	94.7
(28, 14)	24.58	96.34	0.26	-77.4	99.3	20.77	97.40	0.21	-82.5	99.0	13.57	80.88	0.17	-71.5	97.3

(a) Portfolios based on individual coins' time-series percentile rank

	L					S					LS				
(j, k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(7, 1)	132.62	120.87	1.10	7653.0	94.6	-60.25	91.34	-0.66	-99.9	99.9	72.04	107.49	0.67	296.3	91.0
(7, 3)	144.47	113.59	1.27	28529.9	93.7	-53.22	92.57	-0.57	-99.8	99.9	91.98	100.46	0.92	2196.1	84.8
(7, 5)	146.05	114.41	1.28	32441.7	96.2	-49.93	94.05	-0.53	-99.8	99.9	98.90	99.00	1.00	4282.6	81.6
(7, 7)	140.26	114.64	1.22	21698.4	95.7	-35.43	94.72	-0.37	-99.5	99.8	118.87	102.75	1.16	13005.8	76.0
(7, 14)	133.41	112.45	1.19	16437.2	95.1	-714.87	227.35	-3.14	-100.0	100.0	62.37	105.32	0.59	103.1	98.4
(14, 1)	104.32	111.98	0.93	1830.0	93.0	-82.67	93.32	-0.89	-100.0	100.0	21.31	102.78	0.21	-85.1	97.1
(14, 3)	112.67	108.85	1.04	4043.8	93.4	-55.12	92.87	-0.59	-99.9	100.0	44.78	97.33	0.46	-10.5	98.0
(14, 5)	118.40	107.76	1.10	6300.4	96.0	-55.02	95.88	-0.57	-99.9	100.0	59.40	96.85	0.61	149.3	98.0
(14, 7)	113.38	109.04	1.04	4476.2	95.3	-28.46	112.51	-0.25	-99.8	99.9	72.73	105.38	0.69	282.4	91.3
(14, 14)	103.44	103.74	1.00	3129.9	94.3	31.68	228.95	0.14	-99.9	100.0	32.26	112.90	0.29	-90.9	97.7
(21, 1)	81.16	112.64	0.72	288.2	98.6	-80.81	90.17	-0.90	-100.0	100.0	0.06	99.14	0.00	-95.8	98.3
(21, 3)	84.95	98.90	0.86	978.5	96.8	-54.77	88.87	-0.62	-99.8	99.9	26.50	80.73	0.33	-35.2	90.3
(21, 5)	83.46	98.09	0.85	927.4	96.7	-58.42	93.02	-0.63	-99.9	100.0	25.51	84.38	0.30	-69.9	96.2
(21, 7)	81.44	96.99	0.84	859.6	95.9	-60.63	97.87	-0.62	-100.0	100.0	31.26	87.93	0.36	-85.1	98.4
(21, 14)	71.25	94.26	0.76	486.6	96.7	-609.17	202.90	-3.00	-100.0	100.0	3.28	82.85	0.04	-90.2	99.4
(28, 1)	91.79	113.21	0.81	640.2	95.3	-97.67	91.22	-1.07	-100.0	100.0	-6.21	95.45	-0.07	-96.7	99.0
(28, 3)	93.53	104.91	0.89	1261.7	94.7	-60.43	90.89	-0.66	-99.9	99.9	32.65	89.13	0.37	-43.0	93.9
(28, 5)	85.52	101.11	0.85	908.2	95.6	-44.73	112.16	-0.40	-99.9	100.0	22.79	86.92	0.26	-79.8	97.4
(28, 7)	74.29	99.29	0.75	436.0	96.0	-67.30	101.19	-0.67	-100.0	100.0	9.14	87.24	0.10	-88.2	96.8
(28, 14)	58.90	96.69	0.61	119.1	97.0	-86.62	111.82	-0.77	-100.0	100.0	0.99	77.82	0.01	-85.7	95.2
Market											78.60	77.79	1.01	2292.9	89.2

(b) Portfolios based on the cross-sectional rank of the time-series percentile ranks

As there are only a handful of coins (less than 10) before 2017, we test cross-sectional momentum using the sample from the beginning of 2017.

5.1 Regression analysis

We measure the returns of all the coins in the sample for a given look-back and holding periods and calculate the cross-sectional percentile rank of those returns so that the coins with the highest returns are assigned 1 and those with the lowest returns are assigned 0. We run a pooled regression of the form

$$k^i_{t,t+k} = \alpha + \beta k^i_{t-j,t} + e^i_t, \tag{17}$$

where $k^i_{t,t+k}$ denotes the cross-sectional percentile rank of coin i's return over the period from t to $t+k$. Table 12 reports the regression results.

Contrary to the results from the time-series regression in the previous section, the majority of the coefficients are negative, suggesting reversal rather than momentum. The reversal pattern is particularly evident when both the look-back and holding periods are short: The magnitude of the coefficient and the t-statistic reach their maximum when $j = 3$ and $k = 1$. The reversal effect tends to diminish in magnitude and significance as the holding period extends, but most coefficients remain negative. While the result largely supports reversal, a few cases have a positive coefficient. Specifically, the one-day look-back period combined with a holding period of 28 days or longer presents a positive coefficient that is statistically significant at the 1% level. However, the magnitude is only 0.007 or smaller. Except for the above cases, none of the positive coefficients is statistically significant.

Liu et al. (2022) observe that cross-sectional momentum works better among bigger coins. Following their observation, we repeat the regression analysis using the top 5% of the coins in terms of market capitalization and report the results in Table 13. Contrary to the previous result from all coins, many coefficients turn positive when only the top 5% of the coins are utilized. The momentum effect is generally stronger when both the look-back and holding periods are short. As both periods extend, the momentum effect diminishes and a negative coefficient appears more frequently. Negative coefficients prevail when the look-back and holding periods are longer than a month, suggesting long-term reversal among large coins.

Given the results above, we examine both reversal and momentum strategies. For the momentum strategy, we select three holding periods for each look-back period up to 28 days that have

Table 12: Regression of cross-sectional momentum

This table reports the results of the cross-sectional momentum regression defined in Equation (17). The dependent variable is the cross-sectional percentile rank of the holding period return, and the independent variable is the cross-sectional percentile rank of the look-back period return. The figures are the estimates of β and Newey-West adjusted t-statistics.

	Holding period (k)										
Look-back (j)	1	3	5	7	14	21	28	35	42	49	56
1	-0.053	-0.033	-0.027	-0.015	-0.004	0.001	0.005	0.007	0.005	0.007	0.006
	(-40.11)	(-25.30)	(-20.57)	(-11.11)	(-3.10)	(0.53)	(3.13)	(4.38)	(3.08)	(4.16)	(3.95)
3	-0.055	-0.042	-0.029	-0.023	-0.007	-0.004	0.003	0.003	0.000	0.002	0.001
	(-41.25)	(-25.50)	(-16.03)	(-11.84)	(-3.46)	(-1.75)	(1.37)	(1.52)	(0.19)	(0.69)	(0.28)
5	-0.054	-0.036	-0.029	-0.025	-0.010	-0.006	0.002	0.000	-0.003	-0.003	-0.004
	(-39.92)	(-19.75)	(-14.45)	(-11.18)	(-4.01)	(-2.34)	(0.65)	(0.06)	(-1.01)	(-0.88)	(-1.26)
7	-0.044	-0.034	-0.029	-0.025	-0.012	-0.008	-0.000	-0.004	-0.006	-0.006	-0.008
	(-32.43)	(-17.62)	(-13.01)	(-10.45)	(-4.22)	(-2.70)	(-0.10)	(-1.19)	(-1.79)	(-1.82)	(-2.39)
14	-0.038	-0.028	-0.025	-0.022	-0.015	-0.008	-0.008	-0.012	-0.015	-0.018	-0.021
	(-27.05)	(-13.32)	(-9.73)	(-7.78)	(-4.38)	(-2.11)	(-1.94)	(-2.85)	(-3.45)	(-3.99)	(-4.59)
21	-0.035	-0.027	-0.024	-0.022	-0.013	-0.013	-0.015	-0.020	-0.025	-0.028	-0.028
	(-23.86)	(-12.19)	(-8.90)	(-7.38)	(-3.33)	(-3.11)	(-3.33)	(-4.22)	(-4.90)	(-5.38)	(-5.23)
28	-0.032	-0.023	-0.019	-0.018	-0.016	-0.019	-0.024	-0.030	-0.035	-0.036	-0.035
	(-21.39)	(-10.45)	(-6.87)	(-5.65)	(-4.07)	(-4.10)	(-4.86)	(-5.76)	(-6.40)	(-6.22)	(-5.88)
35	-0.031	-0.023	-0.022	-0.023	-0.024	-0.027	-0.033	-0.040	-0.042	-0.042	-0.042
	(-19.62)	(-10.03)	(-7.72)	(-7.11)	(-5.64)	(-5.58)	(-6.36)	(-7.25)	(-7.25)	(-6.78)	(-6.53)
42	-0.031	-0.027	-0.027	-0.027	-0.029	-0.033	-0.039	-0.043	-0.045	-0.045	-0.044
	(-19.22)	(-11.37)	(-9.22)	(-8.24)	(-6.71)	(-6.53)	(-7.14)	(-7.40)	(-7.39)	(-7.02)	(-6.57)
49	-0.030	-0.027	-0.028	-0.029	-0.033	-0.037	-0.042	-0.045	-0.047	-0.046	-0.043
	(-18.29)	(-11.27)	(-9.37)	(-8.55)	(-7.43)	(-7.13)	(-7.30)	(-7.39)	(-7.38)	(-6.96)	(-6.16)
56	-0.030	-0.028	-0.030	-0.032	-0.037	-0.039	-0.043	-0.047	-0.047	-0.044	-0.043
	(-17.38)	(-11.48)	(-9.84)	(-9.20)	(-7.91)	(-7.29)	(-7.19)	(-7.39)	(-7.02)	(-6.37)	(-6.00)

Table 13: Regression of cross-sectional momentum (Top 5%)

This table reports the results of the cross-sectional regression using the largest 5% coins. The dependent variable is the cross-sectional percentile rank of the holding period return, and the independent variable is the cross-sectional percentile rank of the look-back period return. The figures are the estimates of β and Newey-West adjusted t-statistics.

	Holding period (k)										
Look-back (j)	1	3	5	7	14	21	28	35	42	49	56
1	0.017	0.039	0.038	0.052	0.060	0.062	0.060	0.057	0.051	0.049	0.048
	(2.95)	(6.57)	(6.12)	(8.35)	(8.71)	(8.36)	(7.48)	(6.79)	(5.74)	(5.29)	(4.90)
3	0.019	0.028	0.041	0.047	0.065	0.066	0.066	0.053	0.048	0.046	0.040
	(3.43)	(3.90)	(5.10)	(5.52)	(6.83)	(6.54)	(6.37)	(4.85)	(4.22)	(3.96)	(3.39)
5	0.009	0.026	0.032	0.035	0.058	0.060	0.061	0.041	0.036	0.036	0.029
	(1.61)	(3.40)	(3.73)	(3.67)	(5.29)	(5.15)	(4.97)	(3.23)	(2.72)	(2.70)	(2.10)
7	0.017	0.025	0.030	0.034	0.060	0.059	0.054	0.034	0.028	0.026	0.020
	(2.98)	(3.07)	(3.18)	(3.31)	(4.97)	(4.59)	(4.02)	(2.39)	(1.96)	(1.82)	(1.34)
14	0.016	0.033	0.041	0.047	0.067	0.058	0.039	0.019	0.013	0.004	-0.001
	(2.61)	(3.91)	(4.00)	(4.10)	(4.86)	(3.76)	(2.31)	(1.09)	(0.75)	(0.24)	(-0.04)
21	0.017	0.032	0.041	0.044	0.054	0.031	0.012	-0.005	-0.015	-0.019	-0.019
	(2.76)	(3.66)	(3.87)	(3.65)	(3.56)	(1.88)	(0.63)	(-0.24)	(-0.74)	(-0.93)	(-0.94)
28	0.012	0.028	0.036	0.033	0.025	0.003	-0.015	-0.032	-0.039	-0.040	-0.037
	(1.90)	(3.18)	(3.36)	(2.69)	(1.58)	(0.17)	(-0.78)	(-1.56)	(-1.86)	(-1.85)	(-1.67)
35	0.005	0.012	0.014	0.010	0.003	-0.017	-0.036	-0.051	-0.053	-0.052	-0.050
	(0.80)	(1.22)	(1.22)	(0.78)	(0.16)	(-0.92)	(-1.79)	(-2.40)	(-2.41)	(-2.28)	(-2.15)
42	0.002	0.006	0.008	0.004	-0.008	-0.031	-0.049	-0.059	-0.058	-0.058	-0.056
	(0.27)	(0.63)	(0.66)	(0.28)	(-0.43)	(-1.56)	(-2.29)	(-2.62)	(-2.55)	(-2.45)	(-2.26)
49	-0.001	0.001	0.003	-0.002	-0.019	-0.043	-0.057	-0.064	-0.064	-0.063	-0.060
	(-0.16)	(0.15)	(0.26)	(-0.17)	(-1.04)	(-2.08)	(-2.58)	(-2.74)	(-2.66)	(-2.56)	(-2.32)
56	-0.005	-0.007	-0.006	-0.012	-0.028	-0.048	-0.063	-0.069	-0.068	-0.066	-0.064
	(-0.65)	(-0.66)	(-0.50)	(-0.86)	(-1.51)	(-2.30)	(-2.74)	(-2.88)	(-2.74)	(-2.56)	(-2.45)

the highest t-statistics in Table 13. Since we construct value-weighted portfolios, the pairs that signal momentum among the top 5% coins are expected to lead to a profitable momentum strategy. Using this criterion, we choose 21 pairs: (1, 7), (1, 14), (1, 21), (3, 14), (3, 21), (3, 28), (5, 14), (5, 21), (5, 28), (7, 14), (7, 21), (7, 28), (14, 5), (14, 7), (14, 14), (21, 3), (21, 5), (21, 7), (28, 3), (28, 5), and (28, 7). For the reversal strategy, we identify three distinct zones: 1) short-term reversal, 2) long-term look-back and short-term holding, and 3) long-term reversal, and choose 12 pairs in these zones: (1, 1), (1, 3), (3, 1), (3, 3), (42, 1), (42, 3), (49, 1), (49, 3), (49, 42), (49, 49), (56, 42), and (56, 49).

5.2 Portfolio analysis

5.2.1 Cross-sectional momentum portfolios

In this section, we analyze the performance of the cross-sectional momentum strategy using the look-back and holding periods selected in the previous section. The coins are sorted on their return over the look-back period and grouped into quintiles. A cross-sectional long-short portfolio is constructed by buying the coins in the highest return quintile (Q5) and shorting the coins in the lowest return quintile (Q1). Table 14 reports the performance of the cross-sectional momentum portfolios. In the table, each row represents a look-back and holding period pair as indicated in the first column, and the columns, L, S, and LS, respectively represent long-only, short-only, and long-short portfolios.

All the long-short portfolios except for the (3, 21) pair have a positive mean return during the sample period. However, even though we select the best 21 pairs from the regression analysis, only eight of them outperform the market in terms of the Sharpe ratio and five have lower MDDs than the market. Moreover, five portfolios, (3, 21), (3, 28), (5, 21), (5, 28), and (7, 28), are liquidated during the sample period. The (1, 7) portfolio performs best in terms of the Sharpe ratio (1.75) and has the lowest MDD of 45.5%. The (14, 5) portfolio earns the highest cumulative return of 543,033%, albeit with a slightly lower Sharpe ratio of 1.41.

To our surprise, the long-only portfolios generally outperform their long-short counterparts in terms of the Sharpe ratio. The Sharpe ratio ranges between 0.95 and 1.62 and is usually greater than that of the market. The (14, 5) portfolio stands out with the highest Sharpe ratio of 1.62 and the highest cumulative return of 267,262%. While the MDDs often exceed those of the long-short portfolios, all long-only portfolios earn a positive profit and outperform their long-short counterparts except for the (1, 7) and (5, 14) pairs. Their standard deviations are also comparable to those of the long-short portfolios. These results suggest that neutralizing market fluctuations by adding short positions is challenging in the cryptocurrency market. Indeed, most short-only portfolios are liquidated during the sample period.

When transaction costs are taken into account (panel (b)), the performance drops significantly especially when the holding period is short due to more frequent rebalancing. The decrease in mean return is particularly pronounced among the long-short portfolios as they require up to twice the transactions required by naked portfolios: With 15 bps transaction costs, the total cost can be as high as 0.6% per rebalancing. After accounting for transaction costs, six long-short portfolios outperform the market in terms of the Sharpe ratio. The (1, 7) portfolio remains the best performer with a Sharpe ratio of 1.31, whereas the (14, 7) portfolio yields the highest cumulative return of 101,218% (Sharpe ratio = 1.28). Nonetheless, it should be noted that three of the seven accounts of both (1, 7) and (14, 7) portfolios are liquidated during the sample period.[16]. If the investment were not distributed over the holding period, these portfolios could be liquidated.

Figure 7 plots log-scale cumulative returns of the (1, 7) and (14, 7) long-short portfolios. Both portfolios perform steadily for most of the sample period. The high volatility before 2018 might be due to the small number of available coins (less than 100) and lack of diversification. Annual performances reported in Table IA9 reveal that the (14, 7) portfolio yields a Sharpe ratio higher than 1.40 every year except for 2018. While the (1, 7) portfolio exhibits a stable performance through most of the sample period, it incurs a significant loss of 50% in July 2023, primarily due to a sharp decline of FantasyGold (FGC). FGC experiences a dramatic increase of 25,719% from June 27 to July 7, and the strategy takes long positions of FGC during this period. It then falls by 71.1% on July 8 and inflicts a significant loss on the strategy. Extreme surges and plunges are rather common in the cryptocurrency market and a single such event can have a drastic impact on the performance of a portfolio. As shown in Table 14, the liquidated portfolios usually have a positive mean return before liquidation, which indicates that they are liquidated not by gradual losses but by a few shocks. Extreme returns should not be ruled out as outliers. Our filtering rule requires both high market capitalization and trading volume and is stricter than those in most previous studies. If smaller or less liquid coins were included, extreme events would occur more frequently.

[16]The number of liquidated accounts and the liquidation dates can be found in Table IA8.

Table 14: Performance of cross-sectional momentum portfolios

This table reports the performance of cross-sectional momentum portfolios of various look-back and holding periods, $(j,\ k)$. 'L', 'S', and 'LS' respectively denote the long-only, short-only, and long-short portfolios, and 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 1, 2017, to August 28, 2023. A transaction cost of 15 bps is assumed.

	L					S					LS				
(j,k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(1, 7)	118.65	96.21	1.23	12091.6	95.0	-40.23	99.59	-0.40	-99.8	100.0	109.96	62.91	1.75	45697.9	45.5
(1, 14)	114.04	95.86	1.19	9110.1	95.2	-70.14	108.88	-0.64	-100.0	100.0	63.16	61.46	1.03	1903.7	61.8
(1, 21)	105.74	94.42	1.12	5563.1	94.8	-1352.78	263.44	-5.14	-100.0	100.0	34.25	104.54	0.33	-75.0	98.4
(3, 14)	112.88	95.03	1.19	8852.6	95.3	-726.89	198.62	-3.66	-100.0	100.0	53.13	76.03	0.70	379.2	97.1
(3, 21)	88.63	93.32	0.95	1801.6	95.2	-570.93	361.14	-1.58	-100.0	100.0	-338.95	292.18	-1.16	-100.0	100.0
(3, 28)	99.21	93.94	1.06	3682.1	94.0	-653.77	235.60	-2.77	-100.0	100.0	10.88	328.70	0.03	-100.0	100.0
(5, 14)	126.55	103.53	1.22	15143.4	95.4	-54.94	121.55	-0.45	-100.0	100.0	122.53	93.54	1.31	16121.8	91.4
(5, 21)	111.50	101.45	1.10	5937.7	93.9	46.26	899.12	0.05	-100.0	100.0	203.81	366.57	0.56	-100.0	100.0
(5, 28)	107.91	102.79	1.05	4363.3	94.2	-693.03	218.44	-3.17	-100.0	100.0	102.55	220.67	0.46	-100.0	100.0
(7, 14)	141.90	113.84	1.25	27066.3	95.6	-2.45	117.59	-0.02	-99.4	100.0	123.86	101.41	1.22	19467.5	87.5
(7, 21)	122.27	113.46	1.08	7178.6	94.4	-992.39	222.39	-4.46	-100.0	100.0	82.33	118.06	0.70	219.6	97.5
(7, 28)	120.89	113.91	1.06	6393.2	94.9	-631.09	252.31	-2.50	-100.0	100.0	135.40	293.56	0.46	-100.0	100.0
(14, 5)	176.29	108.84	1.62	267262.5	92.5	51.78	180.58	0.29	-97.9	99.8	207.47	147.57	1.41	543032.9	90.6
(14, 7)	159.33	105.74	1.51	102953.9	93.3	90.55	232.35	0.39	-98.1	99.8	195.92	136.89	1.43	415219.4	85.5
(14, 14)	131.79	103.36	1.28	19482.5	94.3	-526.27	237.90	-2.21	-100.0	100.0	160.07	162.79	0.98	11370.8	96.5
(21, 3)	163.51	109.25	1.50	109592.0	94.5	-23.37	109.13	-0.21	-99.7	99.9	136.00	102.22	1.33	27826.4	88.8
(21, 5)	139.43	106.14	1.31	26981.9	95.0	-34.90	114.60	-0.30	-99.9	100.0	126.56	110.34	1.15	9132.2	94.9
(21, 7)	124.35	104.41	1.19	10887.4	94.9	-569.53	257.71	-2.21	-100.0	100.0	98.18	111.94	0.88	787.3	98.3
(28, 3)	133.10	108.23	1.23	15132.0	93.6	-46.30	107.78	-0.43	-99.9	100.0	86.45	98.01	0.88	1153.8	95.0
(28, 5)	122.26	105.60	1.16	8592.0	93.8	-39.60	115.71	-0.34	-99.9	100.0	83.36	97.76	0.85	967.7	95.4
(28, 7)	104.49	104.08	1.00	2794.7	94.1	-31.20	122.14	-0.26	-99.9	100.0	58.66	97.25	0.60	98.6	97.6

(a) Performance before transaction costs

	L					S					LS				
(j,k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(1, 7)	105.03	96.20	1.09	4830.9	95.6	-54.43	99.58	-0.55	-99.9	100.0	82.42	62.95	1.31	7227.1	47.3
(1, 14)	107.21	95.85	1.12	5751.9	95.5	-78.02	108.92	-0.72	-100.0	100.0	49.18	61.55	0.80	687.6	62.8
(1, 21)	101.21	94.41	1.07	4091.4	95.0	-1357.04	263.45	-5.15	-100.0	100.0	24.11	104.39	0.23	-87.2	99.1
(3, 14)	106.11	95.02	1.12	5609.2	95.6	-734.00	198.59	-3.70	-100.0	100.0	39.36	76.10	0.52	90.9	97.5
(3, 21)	84.12	93.32	0.90	1309.0	95.7	-577.53	361.17	-1.60	-100.0	100.0	-351.57	290.98	-1.21	-100.0	100.0
(3, 28)	95.79	93.93	1.02	2913.1	94.4	-658.42	235.38	-2.80	-100.0	100.0	3.52	328.68	0.01	-100.0	100.0
(5, 14)	119.89	103.52	1.16	9696.5	95.7	-62.30	121.70	-0.51	-100.0	100.0	108.66	93.52	1.16	6359.1	91.5
(5, 21)	106.98	101.44	1.05	4371.4	94.1	38.12	899.16	0.04	-100.0	100.0	194.01	366.65	0.53	-100.0	100.0
(5, 28)	104.48	102.79	1.02	3452.8	94.4	-698.21	218.38	-3.20	-100.0	100.0	94.18	220.08	0.43	-100.0	100.0
(7, 14)	135.35	113.83	1.19	17485.2	95.9	-9.50	117.64	-0.08	-99.7	100.0	110.19	101.45	1.09	7758.8	89.9
(7, 21)	117.74	113.45	1.04	5288.1	94.6	-997.99	222.40	-4.49	-100.0	100.0	72.74	118.07	0.62	68.4	97.7
(7, 28)	117.47	113.91	1.03	5073.3	95.1	-636.56	252.14	-2.52	-100.0	100.0	126.56	292.82	0.43	-100.0	100.0
(14, 5)	164.99	108.84	1.52	126039.6	93.3	36.81	180.60	0.20	-99.2	99.9	181.03	147.31	1.23	93788.6	92.1
(14, 7)	149.95	105.74	1.42	55166.6	93.9	77.73	231.28	0.34	-99.2	99.9	174.73	136.93	1.28	101218.3	86.5
(14, 14)	125.43	103.35	1.21	12736.2	94.6	-534.08	237.92	-2.24	-100.0	100.0	146.57	162.83	0.90	4553.6	96.6
(21, 3)	150.40	109.26	1.38	45749.4	95.2	-41.68	109.11	-0.38	-99.9	100.0	104.40	102.25	1.02	3304.4	90.9
(21, 5)	129.52	106.14	1.22	13904.9	95.5	-48.24	114.62	-0.42	-100.0	100.0	103.39	110.37	0.94	1870.3	95.7
(21, 7)	116.23	104.41	1.11	6302.3	95.3	-581.68	257.71	-2.26	-100.0	100.0	79.07	112.00	0.71	147.3	98.5
(28, 3)	121.62	108.25	1.12	6987.8	94.3	-63.04	107.82	-0.58	-100.0	100.0	57.98	98.06	0.59	87.4	95.9
(28, 5)	113.67	105.60	1.08	4806.5	94.3	-51.96	115.73	-0.45	-100.0	100.0	62.38	97.77	0.64	163.5	96.0
(28, 7)	97.38	104.08	0.94	1704.0	94.4	-41.58	122.00	-0.34	-100.0	100.0	41.32	97.29	0.42	-37.7	97.9
Market											78.86	77.80	1.01	2333.3	89.1

(b) Performance after transaction costs

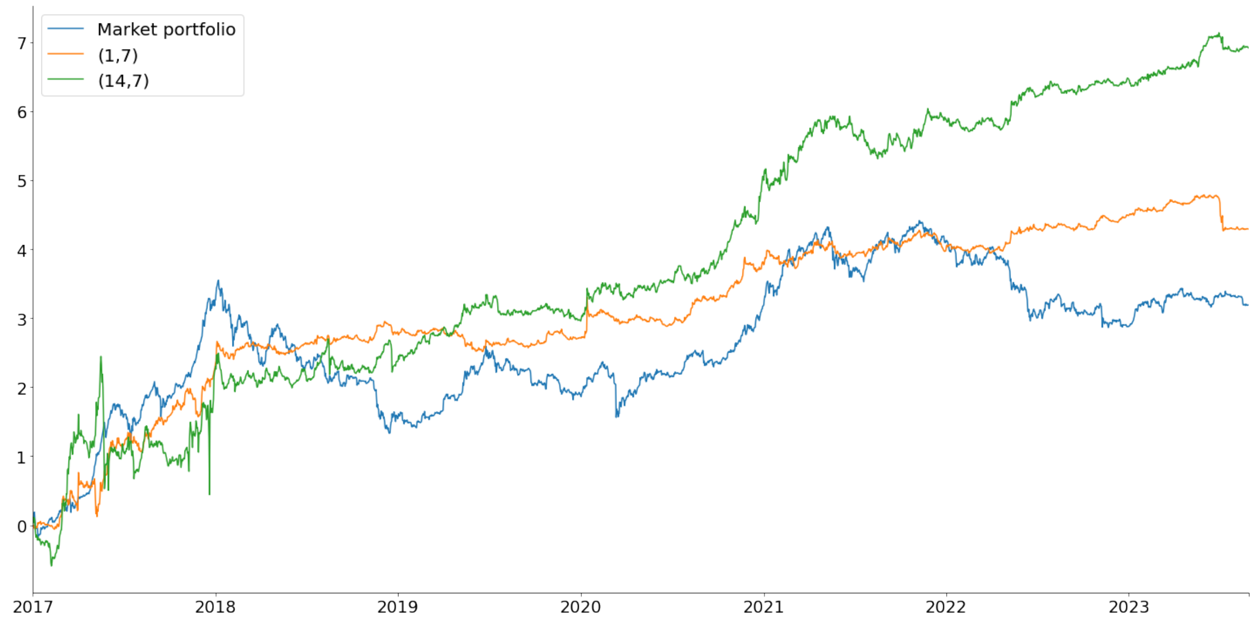


Figure 7: Cross-sectional momentum portfolio log-scale cumulative returns

5.2.2 Cross-sectional momentum portfolios using the top 5%

Next, we analyze momentum portfolios comprising the top 5% of the coins. Since the top 5% contains only a small number of coins; as small as 2 in 2017 and at most 42 in 2021, we divide them into two groups instead of quintiles and make a long-short portfolio by buying the coins above the median and selling those below the median. The results are presented in Table 15.

When the investment pool is confined to the top 5% coins, the long-short portfolios have lower mean returns and standard deviations. As a result, the best-performing portfolios earn significantly lower cumulative returns, but also have lower MDDs. The Sharpe ratios show mixed results with nine of the 21 portfolios yielding higher Sharpe ratios compared to the portfolios of all coins. Five long-short portfolios outperform the market after accounting for transaction costs, of which the (14, 5) portfolio performs best with a Sharpe ratio of 1.40. Even though the portfolios are value-weighted, the results from the full sample are noticeably different from those from the top 5%. This is because the weights are determined by the constituents' relative sizes. If the extreme quintiles contain only small coins, their weights in the portfolio can be significant.

Examining each leg separately, we find that the long-only portfolios yield higher Sharpe ratios in most pairs when only the top 5% coins are utilized. Most long-only portfolios outperform the market in terms of the Sharpe ratio, but they also bear higher MDDs. The (14, 5) long-only portfolio performs best with a Sharpe ratio of 1.54. Unexpectedly, the short-only portfolios fare worse than those from the full sample, which suggests that the losses from the short leg are not confined to jumps of small coins. The majority of short-only portfolios plunge by 99% during the 2017 bull market and another 99% during the 2020 bull market. These results are in line with the findings from the time-series momentum, where the long-only portfolios perform well, while the short-only portfolios perform poorly.

Figure 8 plots selected portfolios' cumulative returns after accounting for transaction costs. The (14, 5) portfolio earns the highest cumulative return, whereas the (1, 7) portfolio has the lowest MDD. Both portfolios perform steadily until early 2021, but they then move sideways generating almost no profits. This result is contrary to what we observe from the full sample. When all coins are utilized, the best-performing portfolios earn profits even in recent periods, despite some large downturns. It appears that the momentum effect among large coins has diminished.

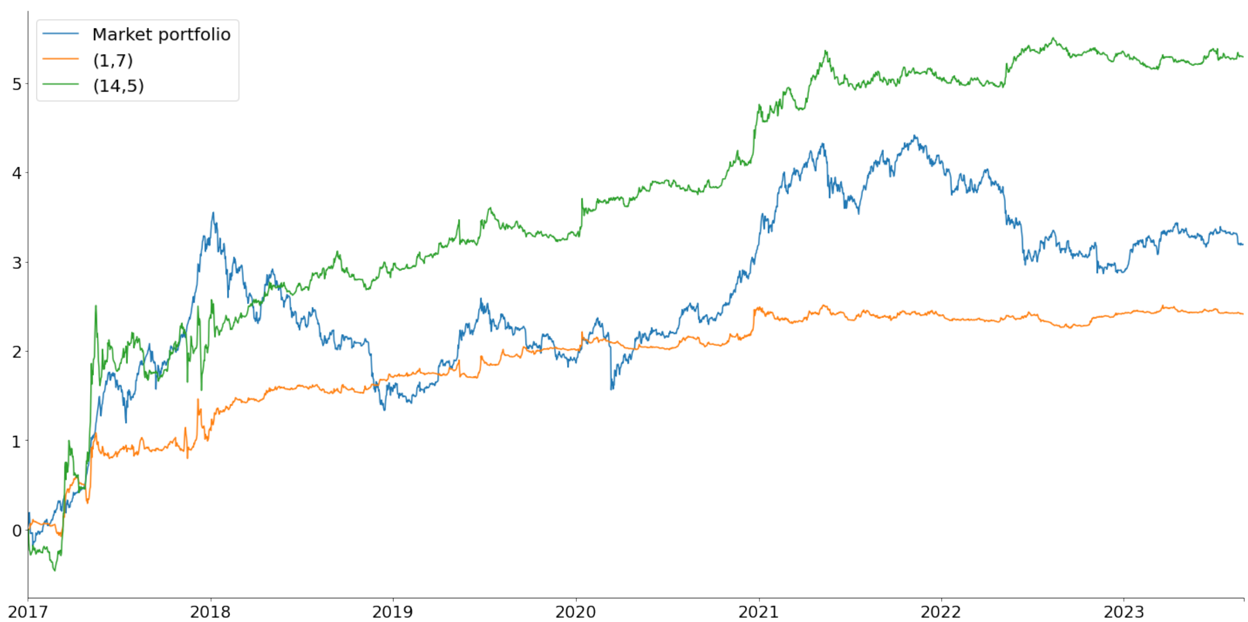


Figure 8: Cross-sectional momentum portfolio log-scale cumulative returns (Top 5%)

5.2.3 Long-term profitability of momentum strategies

In Section 2, we argue that it is necessary to test the significance of log returns to check the long-term profitability of a strategy. Table 16 reports the mean returns and the mean log returns of the cross-sectional momentum long-short portfolios and their t-statistics.

In the case of the portfolios of all coins, ten portfolios' mean returns have a t-statistic greater than 2.0, and three of them pass the cutoff value of 3.0, suggested by Harvey et al. (2016). In

Table 15: Performance of cross-sectional momentum portfolios (Top 5%)

This table reports the performance of cross-sectional momentum portfolios formed of the largest 5% coins. The first column shows the look-back and holding period pairs. 'L', 'S', and 'LS' respectively denote the long-only, short-only, and long-short portfolios, and 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 1, 2017, to August 28, 2023. A transaction cost of 15 bps is assumed.

	L					S					LS				
(j,k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(1, 7)	126.39	87.01	1.45	35693.3	85.6	-69.62	85.00	-0.82	-99.9	100.0	62.12	37.54	1.65	3873.8	36.7
(1, 14)	106.29	84.11	1.26	10756.9	88.8	-90.05	99.22	-0.91	-100.0	100.0	29.12	41.55	0.70	288.6	69.6
(1, 21)	96.43	84.36	1.14	5429.1	89.2	358.41	1119.47	0.32	-100.0	100.0	26.03	125.12	0.21	-68.7	92.4
(3, 14)	116.95	87.59	1.34	18339.8	89.2	-83.50	99.37	-0.84	-100.0	100.0	47.44	61.42	0.77	574.5	92.6
(3, 21)	99.94	84.25	1.19	6937.4	88.8	147.09	957.97	0.15	-100.0	100.0	38.13	71.31	0.53	109.9	82.3
(3, 28)	104.23	86.13	1.21	8494.2	91.4	-914.32	230.20	-3.97	-100.0	100.0	-173.86	231.97	-0.75	-100.0	100.0
(5, 14)	122.30	88.71	1.38	24742.7	88.6	-95.86	105.27	-0.91	-100.0	100.0	58.68	62.43	0.94	1300.7	85.9
(5, 21)	110.13	87.77	1.25	11319.6	90.0	-352.62	520.44	-0.68	-100.0	100.0	42.30	90.08	0.47	-22.1	97.8
(5, 28)	104.92	86.36	1.21	8787.9	91.3	-896.11	234.93	-3.81	-100.0	100.0	4682.61	4906.62	0.95	-100.0	100.0
(7, 14)	126.72	88.89	1.43	32984.1	88.3	-80.98	107.45	-0.75	-99.9	100.0	70.73	64.95	1.09	2648.3	75.2
(7, 21)	107.75	89.49	1.20	8834.4	90.3	-319.77	465.01	-0.69	-100.0	100.0	42.60	99.05	0.43	-46.3	97.4
(7, 28)	104.58	87.67	1.19	8021.9	90.6	-787.74	248.13	-3.17	-100.0	100.0	10093.71	7890.21	1.28	-100.0	100.0
(14, 5)	156.56	97.30	1.61	152330.6	87.4	-32.35	87.16	-0.37	-99.1	99.7	124.58	77.19	1.61	59396.3	60.9
(14, 7)	151.11	96.10	1.57	113607.4	87.7	-41.42	87.31	-0.47	-99.5	99.8	112.48	75.00	1.50	29285.6	65.0
(14, 14)	121.21	91.49	1.32	19768.8	88.4	-72.80	97.58	-0.75	-100.0	100.0	70.09	72.46	0.97	1771.6	86.5
(21, 3)	151.04	98.48	1.53	97650.4	87.4	-36.76	86.67	-0.42	-99.3	99.8	110.70	77.06	1.44	23814.3	78.0
(21, 5)	142.44	97.47	1.46	58177.4	89.1	-50.72	87.29	-0.58	-99.7	99.9	91.68	76.43	1.20	6737.8	81.6
(21, 7)	135.83	96.12	1.41	40324.0	89.4	-63.88	88.16	-0.72	-99.9	100.0	74.69	75.27	0.99	2164.0	83.9
(28, 3)	134.67	97.91	1.38	33384.8	89.1	-54.28	87.53	-0.62	-99.8	99.9	78.31	77.08	1.02	2594.7	87.7
(28, 5)	124.85	96.03	1.30	19193.1	89.9	-64.87	88.64	-0.73	-99.9	100.0	61.38	76.90	0.80	753.5	90.7
(28, 7)	115.57	94.76	1.22	11072.5	90.8	-74.98	89.86	-0.83	-100.0	100.0	44.69	76.65	0.58	178.4	92.0

(a) Performance before transaction costs

	L					S					LS				
(j,k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(1, 7)	117.38	86.99	1.35	19577.9	86.8	-79.78	84.99	-0.94	-100.0	100.0	43.07	37.65	1.14	1016.0	37.6
(1, 14)	101.63	84.10	1.21	7868.2	89.2	-95.85	99.20	-0.97	-100.0	100.0	18.95	41.62	0.46	97.1	70.2
(1, 21)	93.34	84.35	1.11	4406.0	89.6	354.75	1119.48	0.32	-100.0	100.0	17.93	122.94	0.15	-80.9	94.3
(3, 14)	112.38	87.59	1.28	13508.5	89.6	-89.34	99.44	-0.90	-100.0	100.0	37.26	61.46	0.61	241.9	92.8
(3, 21)	96.89	84.24	1.15	5646.4	89.2	141.73	957.99	0.15	-100.0	100.0	31.11	71.25	0.44	31.7	82.3
(3, 28)	101.88	86.13	1.18	7255.7	91.6	-919.15	230.19	-3.99	-100.0	100.0	-179.72	231.99	-0.77	-100.0	100.0
(5, 14)	117.76	88.71	1.33	18269.9	89.1	-101.61	105.36	-0.96	-100.0	100.0	48.73	62.48	0.78	620.6	86.5
(5, 21)	107.02	87.76	1.22	9190.9	90.3	-357.06	520.44	-0.69	-100.0	100.0	34.95	90.05	0.39	-52.4	97.8
(5, 28)	102.63	86.36	1.19	7535.1	91.5	-900.62	234.93	-3.83	-100.0	100.0	4581.56	4811.47	0.95	-100.0	100.0
(7, 14)	122.31	88.89	1.38	24588.7	88.8	-86.53	107.48	-0.81	-100.0	100.0	61.18	64.97	0.94	1355.4	75.5
(7, 28)	102.21	87.67	1.17	6839.0	90.9	-791.96	248.14	-3.19	-100.0	100.0	9941.81	7753.89	1.28	-100.0	100.0
(14, 5)	149.54	97.30	1.54	95458.7	88.2	-41.61	87.16	-0.48	-99.5	99.8	108.15	77.25	1.40	19798.4	61.4
(14, 7)	145.10	96.10	1.51	76161.7	88.3	-49.25	87.32	-0.56	-99.7	99.9	98.54	75.04	1.31	11504.4	67.7
(14, 14)	116.96	91.49	1.28	14876.0	88.8	-78.17	97.59	-0.80	-100.0	100.0	60.50	72.49	0.83	887.2	86.7
(21, 3)	142.97	98.47	1.45	57134.9	88.2	-47.61	86.69	-0.55	-99.7	99.9	91.60	77.16	1.19	6581.8	80.9
(21, 5)	136.34	97.45	1.40	38804.9	89.6	-58.93	87.30	-0.68	-99.9	99.9	77.21	76.46	1.01	2506.1	83.4
(21, 7)	130.71	96.11	1.36	28674.7	89.9	-70.73	88.17	-0.80	-99.9	100.0	62.59	75.31	0.83	909.0	85.2
(28, 3)	127.60	97.91	1.30	20819.9	90.0	-64.24	87.54	-0.73	-99.9	100.0	61.08	77.17	0.79	751.6	89.0
(28, 5)	119.55	96.03	1.24	13467.5	90.5	-72.36	88.66	-0.82	-99.9	100.0	48.42	76.94	0.63	259.4	91.4
(28, 7)	111.09	94.75	1.17	8198.3	91.3	-81.26	89.89	-0.90	-100.0	100.0	33.82	76.68	0.44	34.5	92.6
Market											78.86	77.80	1.01	2333.3	89.1

(b) Performance after transaction costs

contrast, only three mean log returns have a t-statistic greater than 2.0, and none of them passes the cutoff value. Moreover, six mean log returns are negative when the mean returns are positive. Similarly, among the portfolios of the top 5%, six portfolios have a mean return with a t-statistic greater than 2.0, of which none passes the cutoff value. Three mean log returns have a t-statistic greater than 2.0, and four mean log returns are negative when the mean returns are positive. These results demonstrate the true profitability of the cross-sectional momentum strategy that cannot be revealed by the mean return or Sharpe ratio. The mean and the standard deviation of a return are incomplete information when the return is skewed or fat-tailed, and judging a strategy's profitability solely based on them can lead to a wrong conclusion.

Table 16: Cross-sectional momentum portfolio t-test

This table reports the mean daily returns and the mean daily log returns of the cross-sectional momentum long-short portfolios and their Newey-West adjusted t-statistics. A transaction cost of 15 bps is assumed. For liquidated portfolios, the returns before liquidation are used.

	All coins				Top 5%			
	Return		Log return		Return		Log return	
(j, k)	Mean	t-statistic	Mean	t-statistic	Mean	t-statistic	Mean	t-statistic
(1, 7)	0.226	3.453	0.177	2.883	0.118	2.551	0.099	2.261
(1, 14)	0.135	2.044	0.085	1.287	0.052	0.989	0.028	0.511
(1, 21)	0.066	0.721	-0.085	-0.871	0.049	0.484	-0.068	-0.927
(3, 14)	0.108	1.188	0.027	0.275	0.102	1.163	0.051	0.555
(3, 21)	-0.682	-0.998	-1.825	-1.847	0.085	1.371	0.011	0.157
(3, 28)	0.291	0.712	-0.994	-0.838	-0.217	-0.253	-0.987	-0.733
(5, 14)	0.298	2.809	0.172	1.538	0.133	1.583	0.081	0.963
(5, 21)	0.816	1.363	-0.409	-0.702	0.096	1.030	-0.031	-0.224
(5, 28)	0.546	1.207	-0.103	-0.142	12.864	1.069	-0.096	-0.094
(7, 14)	0.302	2.564	0.180	1.675	0.168	2.109	0.110	1.387
(7, 21)	0.199	1.620	0.021	0.163	0.096	1.217	-0.046	-0.376
(7, 28)	0.634	0.963	-0.412	-0.396	27.599	1.384	1.373	1.244
(14, 5)	0.496	3.519	0.282	2.544	0.296	2.955	0.218	2.367
(14, 7)	0.479	3.649	0.285	2.604	0.270	2.804	0.196	2.188
(14, 14)	0.402	2.834	0.158	1.428	0.166	1.915	0.094	1.070
(21, 3)	0.286	2.688	0.145	1.403	0.251	2.438	0.173	1.840
(21, 5)	0.283	2.657	0.123	1.121	0.212	2.222	0.134	1.528
(21, 7)	0.217	2.006	0.037	0.302	0.171	1.964	0.095	1.138
(28, 3)	0.159	1.505	0.026	0.249	0.167	1.902	0.088	1.067
(28, 5)	0.171	1.735	0.040	0.414	0.133	1.606	0.053	0.648
(28, 7)	0.113	1.153	-0.019	-0.197	0.093	1.177	0.012	0.151

5.2.4 Factor regression

This section examines whether Liu et al. (2022) three factors and the continuing overreaction factors can explain cross-sectional momentum. Table 17 reports the results for the (14, 7) long-short portfolio. Examining each factor independently, we find that only the overreaction factors (CS-CO and TS-CO) are significant and the three factors of Liu et al. (2022) are insignificant. The CS-CO factor stands out with a t-statistic of 7.92, which implies an important role of overreaction in explaining cross-sectional momentum. When the return is regressed on all five factors (regression (9)), only the CS-CO factor remains significant with a t-statistic of 4.70. None of these factors or a combination of them can explain the cross-sectional momentum premium: The t-statistic of alpha is greater than 3.0 except when regressed on all five factors, in which case, it is 2.39.

Table 17: Cross-sectional momentum portfolio factor regression

This table reports the factor regression results of the (14, 7) cross-sectional momentum long-short portfolio. The factors are market (MKT), size (SIZE), momentum (MOM), cross-sectional continuing overreaction (CS-CO), and time-series continuing overreaction (TS-CO). The definitions of the factors can be found in Section 4.2.2. The sample period is from January 1, 2017 to August 28, 2023. The t-statistics are Newey-West adjusted t-statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	0.0295	0.0304	0.0234	0.0198	0.0221	0.0293	0.0223	0.0166	0.0127
	(4.29)	(4.38)	(3.86)	(3.06)	(3.37)	(4.44)	(4.34)	(3.05)	(2.39)
MKT	0.0923					0.0805	0.0838	0.0329	-0.0731
	(1.31)					(1.22)	(1.49)	(0.68)	(-1.28)
SIZE		0.0899				0.0745	-0.0761	-0.1158	-0.1060
		(0.65)				(0.54)	(-0.65)	(-0.99)	(-0.87)
MOM			0.3432				0.3548	0.2286	0.2207
			(1.49)				(1.53)	(1.59)	(1.57)
CS-CO				0.8510				0.7178	0.7001
				(7.92)				(4.75)	(4.70)
TS-CO					0.3298				0.2184
					(2.78)				(1.68)
Adj R^2	0.000	0.003	0.116	0.200	0.024	0.006	0.120	0.242	0.247

5.2.5 Transition probabilities

We analyze transition probabilities to gain deeper insights into the cryptocurrency's return dynamics. Figure 9 shows transition probability heatmaps for various pairs of look-back and holding periods. In the figure, panel (a) displays the transition probability from Q5 to Q4 or Q5, $P(\mathrm{Q5} \to \mathrm{Q4}, \mathrm{Q5})$, and similarly, panels (b), (c), and (d) display $P(\mathrm{Q1} \to \mathrm{Q1}, \mathrm{Q2})$, $P(\mathrm{Q5} \to \mathrm{Q1}, \mathrm{Q2})$, and $P(\mathrm{Q1} \to \mathrm{Q4}, \mathrm{Q5})$, respectively. If momentum prevails, we would observe higher probabilities in panels (a) and (b), whereas if reversal prevails, we would observe higher probabilities in panels (c) and (d). If the transition occurs randomly, $P(\mathrm{Q}_i \to \mathrm{Q}_j, \mathrm{Q}_k)$ would be 40% for all i, j, and k.

The probability $P(\mathrm{Q5} \to \mathrm{Q4}, \mathrm{Q5})$ is below 40% regardless of the look-back and holding periods, whereas $P(\mathrm{Q5} \to \mathrm{Q1}, \mathrm{Q2})$ is higher than 40% for all the periods, which implies that the coins with higher returns in the look-back period tend to yield lower returns in the holding period. The reversal effect is more pronounced when both look-back and holding periods are less than two weeks or longer than five weeks, and it is weaker when the look-back period is long and the holding period is short. In contrast, the transition from Q1 (panel (b) and (d)) supports momentum especially when the look-back period is less than a week and the holding period is longer than three weeks. Past winners have a strong tendency to become losers, whereas past losers are likely to continue to underperform.

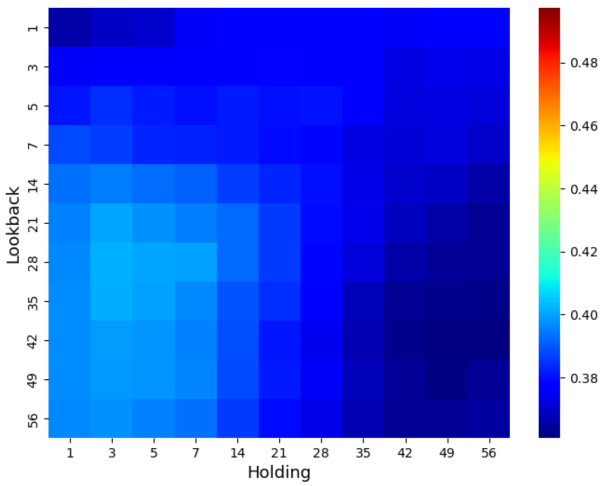
The transition probabilities among the top 5% coins draw a very different picture (Figure 10).[17] Past winners (Q5) exhibit momentum, whereas past losers (Q1) exhibit reversal. The momentum effect among the winners is stronger when the holding period is longer than a week. Meanwhile, the reversal effect among the losers is particularly strong when the look-back and holding periods are longer than three weeks, which suggests long-term reversal among losers.

Overall, the results show that the winners exhibit clearer patterns (reversal among all coins and momentum among large coins), but the transition patterns of the losers are less clear and often opposite to those of the winners, which partly explains why it is difficult to construct a profitable long-short strategy based on past performance. The contrasting results between all coins and large coins imply an interaction between size and momentum in the cryptocurrency market.

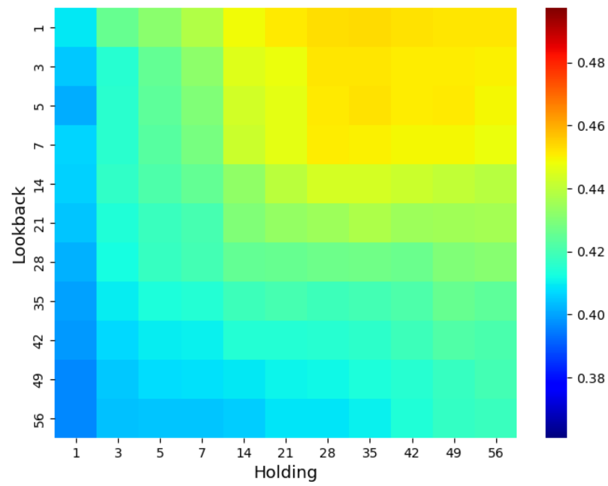
We investigate the transition probabilities more in detail using the (14, 7) strategy. Table 18 reports the transition probabilities (Prob) along with the look-back period return (Mean0), holding period return (Mean), standard deviation (Std), and skewness (Skew). The rows represent the look-back period quintiles and the columns the holding period quintiles.

In the case of all coins (panel (a)), the transition probability $P(\text{Q5} \to \text{Q1})$ is higher than $P(\text{Q5} \to \text{Q5})$ (29.26% vs 23.52%), which suggests reversal among winners. Interestingly, the coins that transit from Q5 to Q1 earn higher returns during the look-back period than those that transit to Q5 (50.65% vs. 39.83%). It appears that while many past winners remain winners in the future, those that appreciate most tend to fall sharply during the holding period. The transition probability from Q1 to Q1 is higher than that from Q1 to Q5 (23.83% vs 20.63%), which suggests momentum among losers. Although past losers are less likely to become winners, some of them jump aggressively during the holding period as evidenced by the extremely high standard deviation (270.44%) and skewness (81.54). As mentioned in Section 3.2, there are 136 coins in the sample that fall for five consecutive days before surging more than 50% the following day. Such jumps are the main cause of the liquidation of most short-only portfolios. Coins in both Q1 and Q5 are more likely to transit to Q1 or Q5 than to the other groups. This result is consistent with the bimodality of momentum stock returns: Han (2022) finds that both high- and low-momentum stocks have

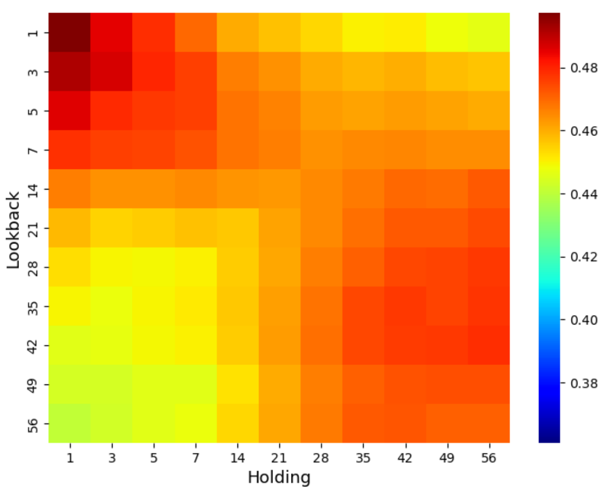
[17]Note the difference in the range of the probability between Figures 9 and 10. The same color represents different probabilities.



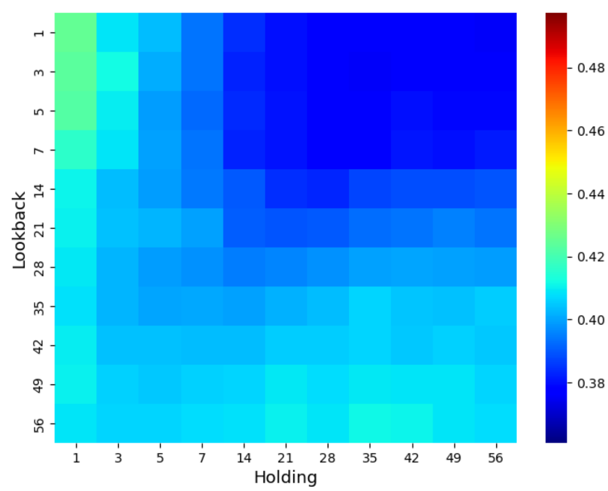
(a) Q5 → Q4,Q5



(b) Q1 → Q1,Q2

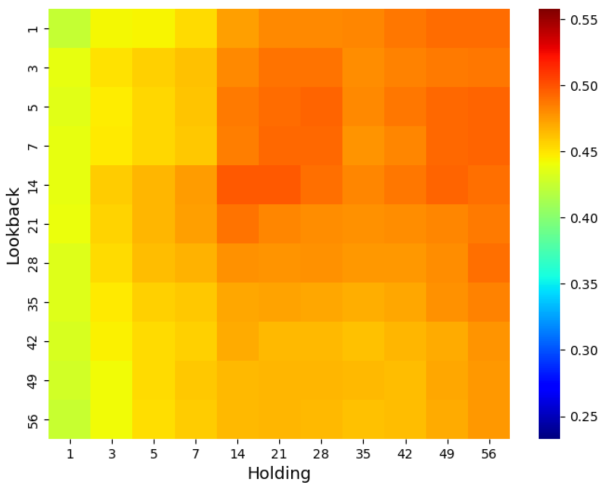


(c) Q5 → Q1,Q2

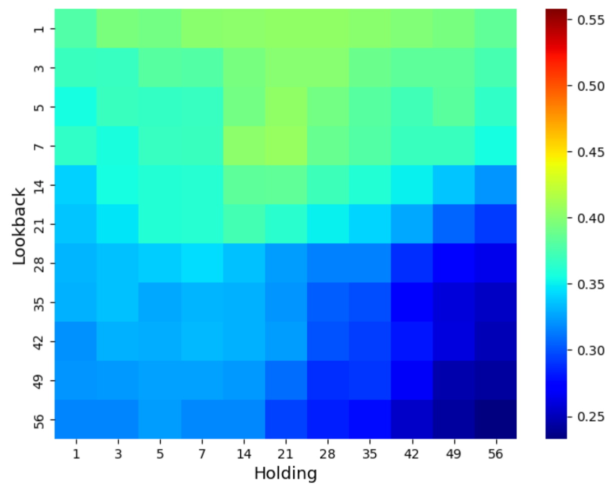


(d) Q1 → Q4,Q5

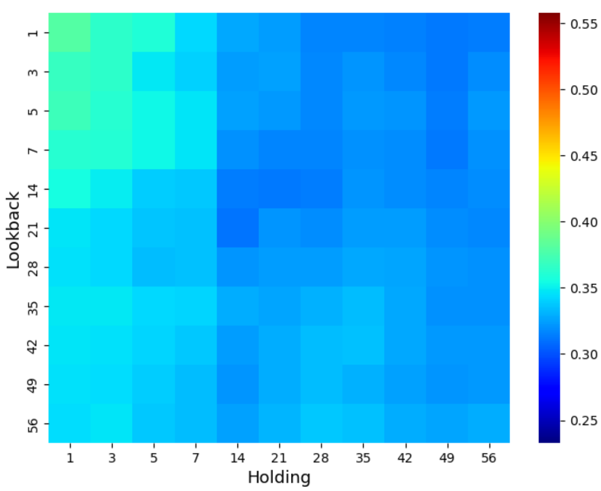
Figure 9: Transition probabilities between look-back and holding period returns of all coins



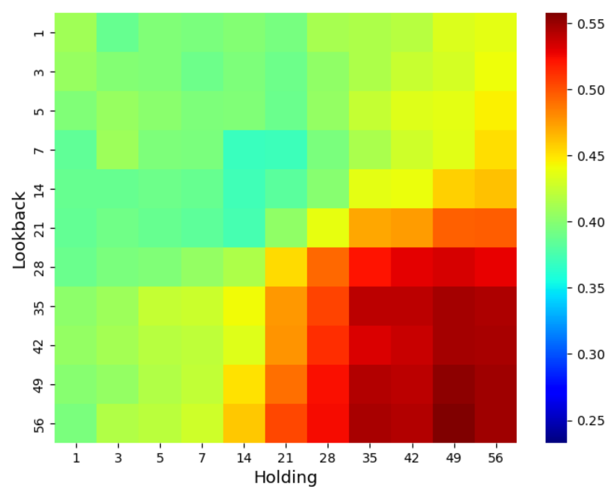
(a) Q5 → Q4,Q5



(b) Q1 → Q1,Q2



(c) Q5 → Q1,Q2



(d) Q1 → Q4,Q5

Figure 10: Transition probabilities between look-back and holding period returns of top 5% coins

nontrivial probabilities for both high and low returns.

Table 18 (b) reports the transition probabilities of the top 5% coins. The transition probability from Q5 to Q5 (27.09%) is significantly higher than the probability to Q1 (14.87%), suggesting strong momentum among large winners. Like the case of all coins, those that transit to Q1 have higher look-back period returns. The probabilities $P(\text{Q1} \to \text{Q1})$ and $P(\text{Q1} \to \text{Q5})$, 13.63% and 15.94%, respectively, are both below 20%, suggesting no momentum or reversal effect among large losers. Although past losers are slightly more likely to become winners, they do not have an extremely high standard deviation or skewness, implying that large losers do not rebound as aggressively as small ones. Overall, the results indicate that momentum is mostly concentrated in large winners.

Table 18: Transition probabilities for the (14, 7) long-short portfolio

This table reports the transition probabilities and return statistics of the (14, 7) cross-sectional momentum long-short portfolio. Rows (columns) indicate the return quintiles in the look-back (holding) period. 'Prob', 'Mean0', 'Mean', 'Std', and 'Skew' respectively denote the transition probability (%), the mean of the look-back period returns (%), and the mean (%), standard deviation (%), and skewness of the holding period returns.

		Q1	Q2	Q3	Q4	Q5
Q1	Prob	23.83	19.00	18.08	18.46	20.63
	Mean0	-22.12	-18.62	-18.43	-19.44	-22.96
	Mean	-15.99	-6.24	-1.49	4.00	26.46
	Std	13.17	11.24	11.84	13.27	270.44
	Skew	-1.09	-0.78	-0.06	0.66	81.54
Q2	Prob	14.29	21.09	23.69	23.03	17.90
	Mean0	-9.45	-8.13	-7.86	-8.19	-8.43
	Mean	-14.84	-6.35	-1.60	4.07	21.30
	Std	12.66	11.06	11.63	12.99	34.32
	Skew	-1.04	-0.76	-0.11	0.70	7.79
Q3	Prob	13.00	21.64	24.39	23.45	17.53
	Mean0	-2.15	-1.95	-1.92	-1.79	-1.24
	Mean	-13.84	-6.15	-1.69	3.63	21.92
	Std	12.34	10.88	11.64	13.00	40.32
	Skew	-1.11	-0.68	-0.10	0.70	22.24
Q4	Prob	16.24	22.09	21.71	21.23	18.73
	Mean0	7.44	5.97	5.08	5.83	7.71
	Mean	-13.77	-6.05	-1.78	3.46	22.97
	Std	11.91	10.89	11.49	13.34	39.79
	Skew	-1.06	-0.71	-0.26	0.64	19.24
Q5	Prob	29.26	17.79	14.27	15.16	23.52
	Mean0	50.65	32.10	31.51	32.41	39.83
	Mean	-15.70	-6.27	-2.17	3.21	27.68
	Std	12.48	11.14	11.88	13.63	41.28
	Skew	-0.98	-0.68	-0.18	0.63	5.05

(a) All coins

		Q1	Q2	Q3	Q4	Q5
Q1	Prob	13.63	22.60	25.05	22.78	15.94
	Mean0	-17.24	-11.78	-11.89	-12.40	-16.56
	Mean	-13.51	-3.10	-0.97	2.50	17.24
	Std	14.76	10.61	11.19	12.77	24.56
	Skew	-1.79	-0.07	-0.24	0.11	3.99
Q2	Prob	6.56	22.38	28.35	26.84	15.87
	Mean0	-4.37	-3.60	-4.19	-5.23	-6.80
	Mean	-10.68	-4.28	-1.61	2.21	14.82
	Std	11.54	10.26	11.45	13.26	26.50
	Skew	-1.76	-0.52	-0.02	1.04	7.34
Q3	Prob	6.47	19.84	28.01	27.53	18.14
	Mean0	1.22	0.81	-0.99	-2.32	-2.55
	Mean	-10.51	-4.57	-0.89	1.83	14.59
	Std	11.50	10.30	11.28	12.35	23.59
	Skew	-0.83	-0.49	0.38	0.43	3.82
Q4	Prob	7.56	20.31	24.46	27.60	20.07
	Mean0	7.96	3.89	2.01	2.81	5.27
	Mean	-11.13	-4.15	-0.98	1.54	13.86
	Std	12.47	10.31	11.00	12.16	27.24
	Skew	-2.08	-0.92	-0.15	0.42	5.31
Q5	Prob	14.87	18.86	18.80	20.37	27.09
	Mean0	80.21	25.68	23.86	22.96	30.55
	Mean	-12.56	-5.17	-2.57	1.47	18.31
	Std	12.55	11.11	12.43	13.44	27.71
	Skew	-1.59	-0.93	-0.27	0.20	2.16

(b) Top 5%

5.2.6 Double sorting

To examine the interplay between size and momentum, we double-sort the coins on size and momentum. Coins are first sorted on size and grouped into quintiles. Within each size group, a long-short portfolio is formed by dividing the coins into quintiles based on their look-back period returns. The (14, 7) strategy is used for portfolio construction as it performs best in the previous analysis. Since coins need to be divided into 25 groups, we require a minimum of 100 coins in the cross-section and start backtesting from December 2017. The results are reported in Table 19.

The momentum strategy works best among the largest coins (M5), followed by the second-largest coins (M4). They respectively yield Sharpe ratios of 1.16 and 0.90 and have the lowest MDDs of 68.3% and 76.9%. They are also the only portfolios that outperform the market. This result reaffirms the stronger momentum effect among larger coins.

Liu et al. (2022) attribute momentum to attention-based overreaction: Limited attention and overconfidence of investors induce a momentum effect among high-attention coins. They employ trading volume and Google search data as indicators of investor attention and find that the momentum effect is concentrated among high-attention coins. Since the cryptocurrency market comprises a small number of well-known large coins and other lesser-known small coins, they argue that large coins attract investor attention more and exhibit stronger momentum.

To test the attention-overreaction hypothesis, we double-sort the coins on volume and momentum and report the results in panel (b). Contrary to the findings of Liu et al. (2022), the coins in the smallest volume groups (V1 and V2) perform best and those in the largest volume group (V5) perform worst. Since the momentum effect is mostly observed among winners, it is worth checking the patterns in the long-only portfolios. Notably, the mean return of the long-only portfolio decreases monotonically with volume and the long-only portfolio of V5 yields a negative mean return.

We examine the behavior of the winners in the largest volume group using transition probabilities (Table IA11). We find that $P(\text{Q5} \rightarrow \text{Q1})$ is much higher at 31.59% than $P(\text{Q5} \rightarrow \text{Q5})$ of 22.20%. The coins that transit to Q1 also record a significantly higher return of 69.96% during the look-back period and are smaller with an average market capitalization of 522.3 million USD, compared to those that transit to Q5, which yield a look-back period return of 46.94% and have an average market capitalization of 1,091.2 million USD. This result implies that relatively small coins that receive unusually high attention and surge tend to fall sharply in the short run, causing reversal rather than momentum. We do not rule out overreaction as the underlying mechanism of momentum. The long-term reversal effect is consistent with the overreaction hypothesis. However, whether overreaction is caused by attention is questionable.

To test whether the momentum effect is more pronounced among overreacted coins, we double-sort the coins on continuing overreaction (CO) and momentum and report the results in panel (c). While the long-short portfolios do not exhibit a distinct pattern, we observe from the long-only portfolios that the performance improves with CO until CO4 and then suddenly drops in CO5. The short-only portfolios have the opposite trend: the performance worsens with CO until CO4 and then improves in CO5. The increasing mean return of the long-only portfolios is consistent with the overreaction hypothesis. A potential explanation for the distinct behavior of CO5 is that when coins surge exceptionally for a prolonged period, investors realize profits causing them to fall in the short run. Meanwhile, when coins plunge exceptionally for a prolonged period, investors lose interest in them and the coins lose momentum to rebound. The inconsistent patterns between winners and losers make it difficult to explain momentum using a single mechanism.

5.2.7 Summary of findings and discussion

In our analysis so far, we observe that buying (large) coins with higher past returns yields profits. Conversely, short-selling those with lower returns is subject to high jump risks and incurs losses. Using a long-short strategy in pursuit of market-neutral performance is generally ineffective in the cryptocurrency market. Several pairs of look-back and holding periods render profitable momentum strategies. However, only a couple of them yield a statistically significant mean log return. The characteristics of momentum are very different in the cryptocurrency market compared to the equity market. While the momentum profit originates mainly from the short leg and small stocks in the equity market, it originates mainly from the long leg and large coins in the cryptocurrency market.

Regarding the underlying mechanism of momentum, we do not find a single mechanism that is consistent with our findings. Overreaction is a likely cause of momentum: We observe long-term reversal; the cryptocurrency market is dominated by retail investors, who are more prone to overreaction; the momentum effect is stronger among winners with a higher continuing overreaction measure; the sheer fact that three-digit returns are not uncommon is clear evidence of overreaction. However, the overreaction period varies across coins, and overreaction followed by correction can also cause reversal for the same holding period: Winners with a higher trading volume tend to fall in the short run; winners in the highest overreaction group perform poorly; losers frequently

Table 19: Performance of cross-sectional momentum in different coin groups

This table reports the performance of the (14, 7) cross-sectional momentum long-short portfolio in different coin groups. Coins are grouped on size (panel (a)), trading volume (panel (b)), or continuing overreaction (panel (c)), and a (14, 7) long-short portfolio is formed within each group. Coins are value-weighted when grouped on size or continuing overreaction, and volume-weighted when grouped on volume. 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from December 1, 2017, to August 28, 2023. A transaction cost of 15 bps is assumed.

	L					S					LS				
Group	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
M1	7.62	125.92	0.06	-97.5	99.7	35.53	105.82	0.34	-74.0	98.4	35.36	98.69	0.36	-47.8	97.1
M2	34.63	105.34	0.33	-71.3	98.6	-22.28	108.44	-0.21	-99.2	99.5	35.36	82.91	0.43	7.3	93.8
M3	-0.42	98.89	-0.00	-94.4	99.1	-2.10	98.25	-0.02	-94.5	97.3	18.70	70.26	0.27	-27.7	89.0
M4	40.32	101.85	0.40	-49.6	98.4	5.58	97.52	0.06	-91.1	97.3	60.28	67.21	0.90	803.3	76.9
M5	84.36	98.53	0.86	704.4	94.6	3.28	101.43	0.03	-94.6	98.9	91.18	78.59	1.16	3171.2	68.3
Market											40.66	76.65	0.53	83.5	89.1

(a) Double sorting on size and momentum

	L					S					LS				
Group	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
V1	52.33	91.25	0.57	80.5	97.0	-18.74	100.28	-0.19	-98.1	99.8	66.97	74.16	0.90	890.0	74.5
V2	56.81	97.28	0.58	71.9	97.8	13.07	94.89	0.14	-83.6	95.7	75.69	66.23	1.14	2039.8	78.0
V3	36.27	99.87	0.36	-56.1	98.8	-14.17	102.36	-0.14	-98.3	99.5	30.70	76.26	0.40	11.7	88.2
V4	22.68	105.10	0.22	-85.3	98.7	-10.88	108.62	-0.10	-98.2	99.4	38.33	78.26	0.49	59.4	85.7
V5	-1.36	110.56	-0.01	-97.2	99.1	1.99	110.26	0.02	-97.0	99.3	6.79	93.78	0.07	-87.4	93.4
Market											40.66	76.65	0.53	83.5	89.1

(b) Double sorting on volume and momentum

	L					S					LS				
Group	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
CO1	53.79	90.08	0.60	105.7	93.0	79.83	106.03	0.75	228.0	90.5	131.87	75.52	1.75	35756.7	61.8
CO2	41.32	89.18	0.46	7.6	94.8	9.68	98.88	0.10	-89.6	95.6	62.65	70.72	0.89	768.6	73.3
CO3	85.70	105.70	0.81	522.6	97.7	-24.26	95.12	-0.26	-98.1	99.0	79.01	92.38	0.86	841.0	80.3
CO4	128.31	106.01	1.21	6189.0	97.7	-84.92	103.54	-0.82	-100.0	100.0	126.62	95.31	1.33	10904.4	76.6
CO5	1.25	123.01	0.01	-98.4	99.4	-13.87	96.28	-0.14	-97.0	98.9	0.93	102.65	0.01	-94.0	95.2
Market											40.66	76.65	0.53	83.5	89.1

(c) Double sorting on continuing overreaction and momentum rebound.

Our findings do not support the attention-based explanation. The momentum portfolio formed of higher volume coins (high attention coins) underperforms that of lower volume coins (low attention coins). In particular, the performance of the long-only portfolio, where the momentum effect is concentrated, worsens monotonically with volume. Coins with high volume relative to their size are likely those that receive unusually high attention. When coins are sorted on relative volume (Table IA12), both long-only and short-only portfolios in the highest relative volume group perform very poorly. These results contradict the attention-based explanation. We also do not find evidence that the momentum strategy performs better during a high-attention period. In an unreported analysis, we regress the return of the (14, 7) long-short portfolio on the total trading volume during the look-back period and find that the coefficient is insignificantly negative.

A plausible explanation for the difference in the performance of large and small coins is the different composition of investors. Speculators and retail investors prefer small coins for their high volatility and potential jackpot returns, whereas institutional investors and long-term investors choose major coins for their liquidity and relative stability. The average volatility of daily trading volume changes of the largest 5% coins is 74.9%, significantly lower than that of the rest, 130.53%, which implies that small coins are the main target of speculators and retail investors pursuing a jackpot. Speculators trade more frequently to realize profits. Such activities can make the price continuation of small coins short-lived and cause reversal.

The cryptocurrency market is fundamentally community-driven, bearing similarities to social media platforms. In the stock market, stocks that are the talk of social media communities—so-called meme stocks—allow small investors to collectively behave like a singular, large trader with the potential to manipulate prices. Analogous strategies are evident in the cryptocurrency market, often labeled as "pump-and-dump" schemes. These are coordinated social trading efforts aimed at inducing short-term price spikes. Such price fluctuations should not be mistaken for genuine momentum effects. Cryptocurrency's price dynamics are uniquely influenced by its close ties to online communities and real-time information flow via social media. This distinct interplay between online sentiments and price dynamics differentiates the momentum behaviors of cryptocurrencies from those of traditional assets. Minor coins are more susceptible to sentiment changes and their price continuation and reversal are far less predictable, making it difficult to detect momentum effects in these coins.

5.3 Further analysis

This section conducts various analyses to better understand cross-sectional momentum in the cryptocurrency market. All the results presented in this section take transaction costs into account. The results of the reversal strategy can be found in the Internet Appendix.

5.3.1 Different weighting schemes

This section explores different weighting schemes. The results are reported in Table 20, where the rows, Value, CapValue, Volume, CapVolume, and Equal respectively denote value-, capped-value-, volume-, capped-volume-, and equal-weighted portfolios. The results for all the look-back and holding periods are reported in Table IA14.

The value-weighted portfolio outperforms the volume-weighted portfolio in both (1, 7) and (14, 7) strategies. The value-weighted portfolio has a higher Sharpe ratio and a lower MDD. As large major coins usually have a high trading volume, the inferior performance of the volume-weighted portfolio can be attributed to the minor coins, whose trading volume has suddenly surged. The elevated standard deviations of the volume-weighted portfolios suggest that such minor coins' future movement is unpredictable. This result is consistent with the finding in Section 5.2.6 that the coins in the highest volume group perform worst, and provides additional evidence that limited attention is an unlikely cause of momentum. The equal-weight portfolio performs worst in both strategies. This result has been anticipated as the momentum effect is stronger among large coins. When the weights are capped, the MDD decreases as the weights are less concentrated, but the overall performance tends to deteriorate, perhaps because the weights of the largest coins are reduced.

Table 20: Performance of cross-section momentum under different weighting schemes

This table reports the performance of the (1, 7) and (14, 7) cross-sectional momentum long-short portfolios under different weighting schemes: value-weight (Value), volume-weight (Volume), capped-value-weight (CapValue), capped-volume-weight (CapVolume), and equal-weight (Equal). 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 1, 2017, to August 28, 2023. A transaction cost of 15 bps is assumed.

	(1, 7)					(14, 7)				
Scheme	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
Value	82.42	62.95	1.31	7227.1	47.3	174.73	136.93	1.28	101218.3	86.5
CapValue	74.57	55.17	1.35	5578.7	39.2	113.42	95.95	1.18	9334.3	85.3
Volume	61.36	106.36	0.58	78.7	98.0	231.64	240.91	0.96	35454.4	92.1
CapVolume	27.03	65.45	0.41	53.0	86.9	49.63	96.06	0.52	30.1	89.4
Equal	10.65	40.56	0.26	18.7	91.9	55.87	73.44	0.76	569.9	84.4
Market						78.86	77.80	1.01	2333.3	89.1

5.3.2 Binance futures

In the cryptocurrency market, investors can take short positions only in the futures market. Also, futures markets are more liquid than spot markets, and the coins traded in the futures market are relatively large and liquid. Hence, we test the cross-sectional momentum strategy using the coins listed on the Binance futures market. We obtain futures price and trading volume data from Binance's website.[18] The dataset contains 239 unique coins, and starts on September 8, 2019 and ends on November 17, 2023. We require a minimum of 20 coins to be included in the sample, and the backtesting period starts on February 12, 2020. Table 21 reports the performance of the cross-sectional momentum portfolios formed of the coins listed on the Binance futures market.

Most long-short portfolios earn profits and six of them outperform the market. They also have smaller MDDs than the market. The (5, 21) and (7, 28) strategies perform best with Sharpe ratios of 1.32 and 1.21, respectively. Nevertheless, the cumulative returns in Figure 11 reveal that most profits are accumulated before 2022 and they perform poorly since then. This result is in line with our earlier observation that a cross-sectional momentum portfolio formed of the top 5% does not perform well since 2021. The previous best strategy, (14, 7), performs comparably to the market with a Sharpe ratio of 0.83, whereas the (1, 7) strategy with the lowest MDD now has the highest MDD of 78.7%. This inconsistency reveals the unreliability and fragility of the findings in this paper and perhaps in many other papers on cryptocurrency. Although we do our best to conduct our analysis as thoroughly and rigorously as possible, the volatile nature of cryptocurrencies and their short history make it difficult to obtain robust findings. The cryptocurrency market is still immature and evolving fast. The findings in this study may prove to be wrong in the future.

5.3.3 Skipping the last day in the look-back period

In the regression analysis, we observe a strong reversal effect when the look-back period is one day. Therefore, we test momentum strategies skipping the last day in the look-back period, similarly to the momentum strategy of Jegadeesh and Titman (1993) that skips the last month. The results are reported in Table 22.

When the last day is omitted in the look-back period, the performance generally improves: 12 out of the 18 long-short portfolios yield higher Sharpe ratios. However, the conclusion is not definitive. For instance, the (14, 7) portfolio's Sharpe ratio improves from 1.28 to 1.33, but the cumulative return decreases from 101,218% to 37,389%.

[18] `https://data.binance.vision/?prefix=data/futures/cm/daily/klines/`

Table 21: Performance of cross-sectional momentum portfolios (Binance futures)

This table reports the performance of cross-sectional momentum portfolios formed of the coins listed on the Binance futures market. ‘L’, ‘S’, and ‘LS’ respectively denote the long-only, short-only, and long-short portfolios, and ‘Mean’, ‘Std’, ‘Sharpe’, ‘Cum’, and ‘MDD’ respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from February 12, 2020, to August 28, 2023. A transaction cost of 15 bps is assumed.

	L					S					LS				
(j, k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(1, 7)	54.91	86.11	0.64	84.6	89.4	-51.55	90.32	-0.57	-96.9	99.0	-14.97	37.24	-0.40	-56.5	78.7
(1, 14)	58.76	86.15	0.68	113.1	85.5	-74.87	93.48	-0.80	-98.9	99.8	-14.16	40.11	-0.35	-58.9	72.5
(1, 21)	68.25	85.82	0.80	209.5	83.7	-54.36	98.69	-0.55	-97.9	99.4	12.70	43.21	0.29	12.8	66.8
(3, 14)	76.29	86.81	0.88	305.4	82.6	-79.32	98.56	-0.80	-99.2	99.7	6.47	40.94	0.16	-7.0	53.1
(3, 21)	77.78	89.20	0.87	295.9	85.4	-52.72	95.49	-0.55	-97.5	98.7	43.85	44.10	0.99	262.5	36.3
(3, 28)	69.66	86.67	0.80	219.6	84.3	-47.14	95.26	-0.49	-96.9	99.2	27.82	40.72	0.68	108.9	42.6
(5, 14)	93.09	90.03	1.03	589.8	82.4	-54.63	97.51	-0.56	-97.9	99.3	43.22	53.38	0.81	200.3	44.6
(5, 21)	93.13	89.07	1.05	611.9	87.2	-32.68	92.35	-0.35	-94.1	96.9	69.00	52.45	1.32	708.8	55.4
(5, 28)	84.68	91.22	0.93	381.8	81.3	-25.23	92.70	-0.27	-92.1	97.6	53.48	49.52	1.08	375.4	39.0
(7, 14)	87.00	89.63	0.97	457.6	87.1	-62.81	101.21	-0.62	-98.7	99.4	35.12	56.11	0.63	109.9	49.6
(7, 21)	64.76	88.81	0.73	142.1	90.1	-43.83	101.38	-0.43	-97.4	98.6	32.21	52.26	0.62	102.2	56.5
(7, 28)	81.24	90.55	0.90	331.6	84.5	-12.37	95.04	-0.13	-88.2	97.8	61.30	50.76	1.21	522.4	34.4
(14, 5)	97.14	91.01	1.07	683.2	86.7	-30.44	96.70	-0.31	-94.4	98.4	59.08	68.13	0.87	290.9	54.9
(14, 7)	94.54	90.44	1.05	623.8	87.5	-35.61	96.07	-0.37	-95.4	98.3	52.61	63.68	0.83	240.4	56.4
(14, 14)	85.60	90.53	0.95	416.5	88.5	-33.46	97.82	-0.34	-95.3	98.0	45.30	61.54	0.74	171.7	62.4
(21, 3)	103.98	91.42	1.14	911.2	88.9	-41.13	100.68	-0.41	-96.9	98.4	54.12	71.60	0.76	194.9	71.7
(21, 5)	97.71	90.51	1.08	722.4	88.1	-43.08	98.04	-0.44	-96.8	98.4	41.38	67.46	0.61	101.7	64.9
(21, 7)	93.89	90.49	1.04	612.8	87.2	-42.46	96.83	-0.44	-96.6	98.4	41.44	65.14	0.64	114.4	56.7
(28, 3)	90.48	94.28	0.96	445.4	88.3	-46.64	97.82	-0.48	-97.2	99.0	39.93	69.70	0.57	80.8	55.5
(28, 5)	85.98	93.94	0.92	366.0	88.2	-38.10	96.36	-0.40	-95.8	98.7	41.83	67.04	0.62	108.3	52.4
(28, 7)	77.86	93.13	0.84	252.5	87.8	-41.51	96.97	-0.43	-96.5	98.7	33.88	65.66	0.52	58.2	52.3
Market											60.66	73.85	0.82	238.1	78.5

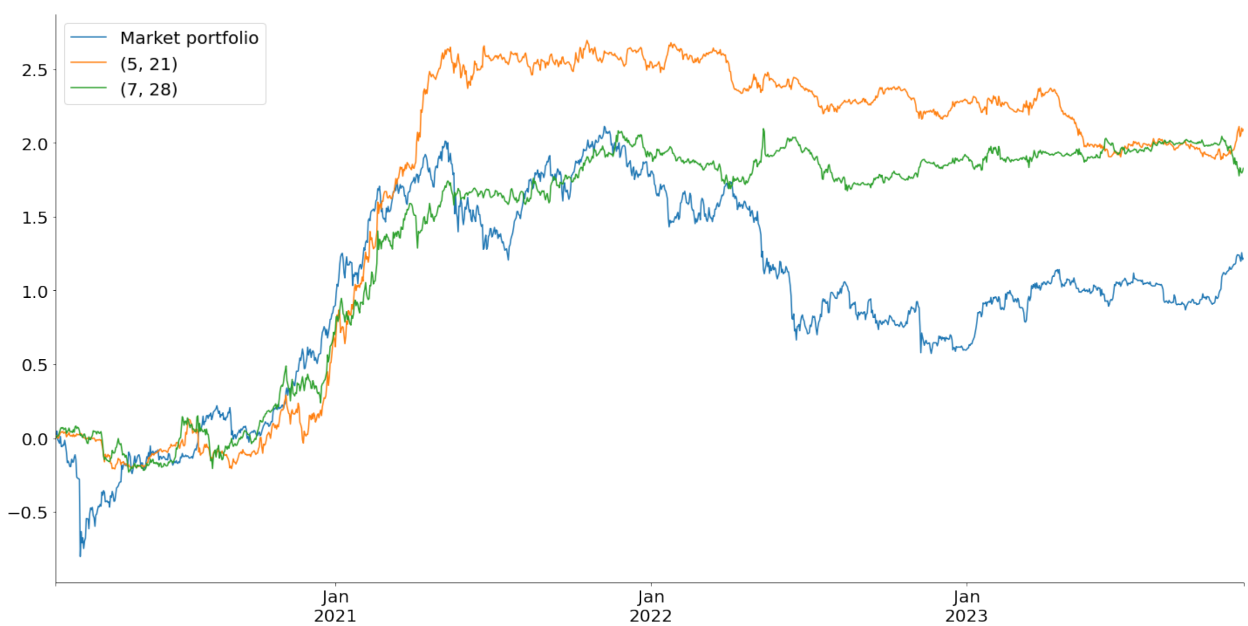


Figure 11: Cross-sectional momentum portfolio log-scale cumulative returns (Binance futures)

Table 22: Performance of cross-sectional momentum portfolios (last day of the look-back period omitted)

This table reports the performance of cross-sectional momentum portfolios when the last day is omitted in the look-back period. 'L', 'S', and 'LS' respectively denote the long-only, short-only, and long-short portfolios, and 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 1, 2017 to August 28, 2023. A transaction cost of 15 bps is assumed.

	L					S					LS				
(j, k)	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD	Mean	Std	Sharpe	Cum	MDD
(3, 14)	99.48	95.72	1.04	3470.7	96.9	-47.04	142.70	-0.33	-100.0	100.0	82.45	96.15	0.86	1042.6	87.5
(3, 21)	88.17	94.19	0.94	1690.8	96.3	-381.79	294.10	-1.30	-100.0	100.0	-205.06	260.90	-0.79	-100.0	100.0
(3, 28)	84.59	94.65	0.89	1291.1	96.6	-1439.25	270.43	-5.32	-100.0	100.0	41.53	111.01	0.37	-62.8	97.4
(5, 14)	114.82	99.25	1.16	8354.8	96.0	-625.26	250.31	-2.50	-100.0	100.0	96.64	76.30	1.27	9280.8	61.9
(5, 21)	98.96	98.86	1.00	2838.2	94.4	-627.52	205.36	-3.06	-100.0	100.0	510.06	1073.48	0.48	75201.5	86.8
(5, 28)	97.96	100.16	0.98	2442.0	95.8	-565.63	253.64	-2.23	-100.0	100.0	-178.59	235.31	-0.76	-100.0	100.0
(7, 14)	130.43	113.06	1.15	13137.4	96.0	-680.85	217.89	-3.12	-100.0	100.0	115.58	94.00	1.23	17062.5	68.4
(7, 21)	113.21	113.23	1.00	3914.2	95.4	-642.02	217.49	-2.95	-100.0	100.0	95.14	115.78	0.82	1253.7	96.2
(7, 28)	105.19	114.16	0.92	2100.9	95.9	-1205.84	287.16	-4.20	-100.0	100.0	-143.30	300.87	-0.48	-100.0	100.0
(14, 5)	150.48	107.83	1.40	50594.2	93.2	16.59	135.97	0.12	-98.4	99.7	147.34	107.36	1.37	49113.1	87.9
(14, 7)	137.79	104.78	1.31	26030.1	93.6	20.65	141.97	0.15	-98.6	99.7	141.15	106.03	1.33	37389.9	88.5
(14, 14)	116.98	101.63	1.15	7949.0	94.3	-20.50	124.01	-0.17	-99.9	100.0	127.45	110.18	1.16	13757.2	94.9
(21, 3)	124.40	106.70	1.17	9411.9	95.6	-40.34	114.28	-0.35	-99.9	100.0	80.39	102.25	0.79	496.1	95.0
(21, 5)	113.26	104.58	1.08	5050.0	95.9	-27.56	123.71	-0.22	-100.0	100.0	144.03	205.80	0.70	1228.4	97.9
(21, 7)	106.91	103.51	1.03	3520.9	95.2	-767.15	219.49	-3.50	-100.0	100.0	66.63	110.05	0.61	-10.1	98.7
(28, 3)	112.23	106.21	1.06	4269.8	93.2	-44.93	114.77	-0.39	-100.0	100.0	64.02	100.15	0.64	139.5	91.3
(28, 5)	99.20	104.36	0.95	1919.4	94.0	-44.47	119.91	-0.37	-100.0	100.0	49.34	96.76	0.51	16.9	95.5
(28, 7)	87.55	103.41	0.85	877.7	94.1	-70.35	115.86	-0.61	-100.0	100.0	15.73	97.05	0.16	-89.0	98.9
Market											78.86	77.80	1.01	2333.3	89.1

5.3.4 Day-of-the-week effect

In the main analysis, we distribute the investment amount over the holding period. This section examines how the performance varies when investing the entire wealth on a specific day of the week. Table 23 reports the results of the (14, 7) strategy, where rows represent the investment day.

The performance difference across the days of the week is startling. The portfolio investing on Mondays yields the highest Sharpe ratio of 1.43, whereas the portfolios investing on Wednesdays, Thursdays, and Fridays are all liquidated. Even among the portfolios that are not liquidated, the Sharpe ratio varies between 0.81 and 1.43 and the cumulative return varies between 197% and 146,435%. The differences become more evident when we examine the cumulative returns in Figure 12. The discrepancy between the best and the worst portfolios (among not liquidated ones) is not caused by a few events. The worst portfolio consistently underperforms the best one until the end of 2020. This result demonstrates how an empirical study can be unreliable when it assumes rebalancing on a particular day of the week.

Table 23: Performance of cross-sectional momentum under different rebalancing days

This table reports the performance of the (14, 7) cross-sectional momentum long-short portfolio under different rebalancing days. 'Distributed' means investing evenly throughout the week. 'Mean', 'Std', 'Sharpe', 'Cum', and 'MDD' respectively denote the annualized mean return (%), annualized standard deviation (%), annualized Sharpe ratio, cumulative return (%), and maximum drawdown (%). The sample period is from January 1, 2017 to August 28, 2023. A transaction cost of 15 bps is assumed.

	Mean	Std	Sharpe	Cum	MDD
Mon	176.56	123.18	1.43	133392.1	74.1
Tue	92.04	114.09	0.81	197.2	99.4
Wed	238.84	272.98	0.87	-100.0	100.0
Thu	-130.54	296.64	-0.44	-100.0	100.0
Fri	612.34	300.22	2.04	-100.0	100.0
Sat	216.62	200.65	1.08	47418.4	97.2
Sun	217.97	199.17	1.09	146435.3	88.4
Distributed	174.73	136.93	1.28	101218.2	86.5

5.3.5 Leverage and margin mode effects

This section investigates the case of no leverage (1x leverage) and investing 50% of the wealth in each leg of a long-short portfolio. By investing only 50% of the wealth, the portfolio sacrifices potential profits but also has a lower chance of liquidation. It is unclear which investment strategy will perform better. Figure 13 compares the cumulative returns of the (14, 7) strategy under 1x leverage (50% investment) and 2x leverage (full investment).

The 2x leverage portfolio earns a higher cumulative return of 101,218% but has a lower Sharpe

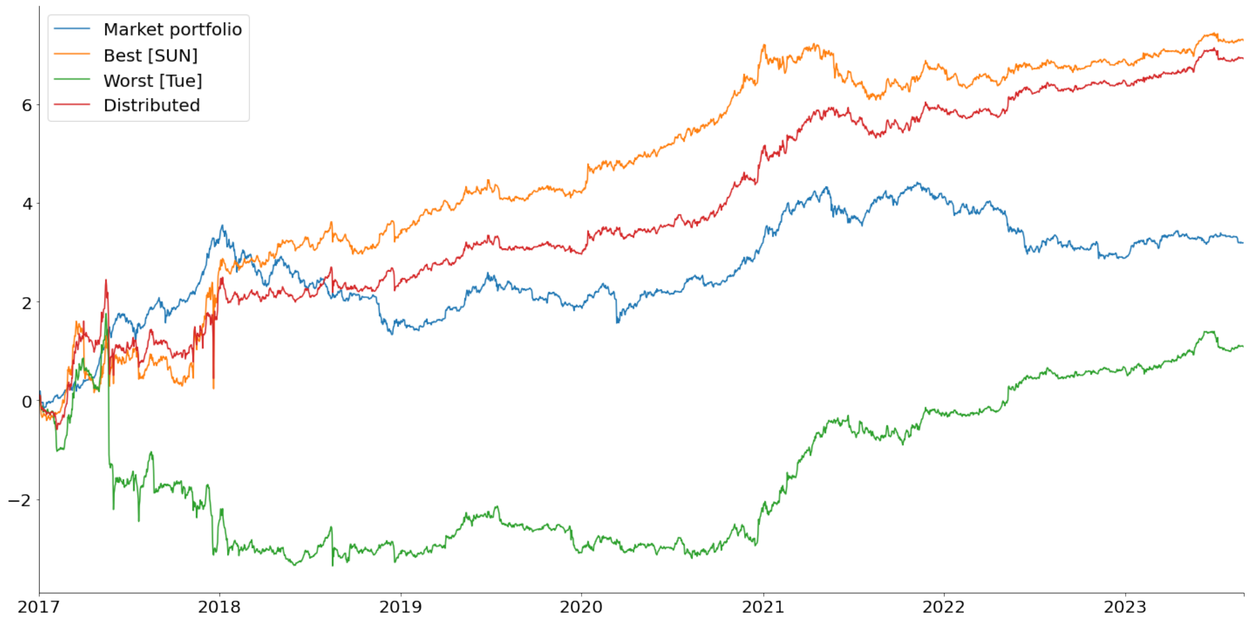


Figure 12: The (14, 7) cross-sectional momentum portfolio cumulative returns under different rebalancing days

ratio of 1.28 compared to the 1x leverage portfolio, whose cumulative return and Sharpe ratio are respectively 4,786% and 1.42. Three accounts of the 2x leverage portfolio are liquidated while no account of the 1x leverage portfolio is liquidated. Considering the high liquidation risk and the investment limit of a leveraged portfolio, a large institutional investor may choose 1x leverage.[19] In such a case, the expected profit can be significantly lower than what the previous results suggest. One may naively think the profit can be maximized by increasing the leverage. However, given the high volatility of cryptocurrencies, the profit can quickly erode as the leverage increases, as shown in Section 2.

Many investors lean towards the cross-margin mode as it can avoid liquidation in particular positions when coins jump or crash momentarily. Yet, there is pronounced tail risk in the cryptocurrency market and a portfolio can suffer a huge loss by a single dramatic event under the cross-margin mode. The isolated-margin mode prevents the propagation of losses at the cost of more frequent liquidation of individual positions. Figure 14 compares the cumulative returns of the (14, 7) momentum strategy under the cross-margin and isolated-margin modes.

Consistent with investor beliefs, the portfolio performs slightly better under the cross-margin mode. The Sharpe ratios are 1.28 (cross-margin) and 1.18 (isolated-margin). While one may make an impetuous conclusion that it is better to tolerate temporal shocks than to realize losses, it should

[19]Recall that the maximum amount a leveraged position can hold is limited.

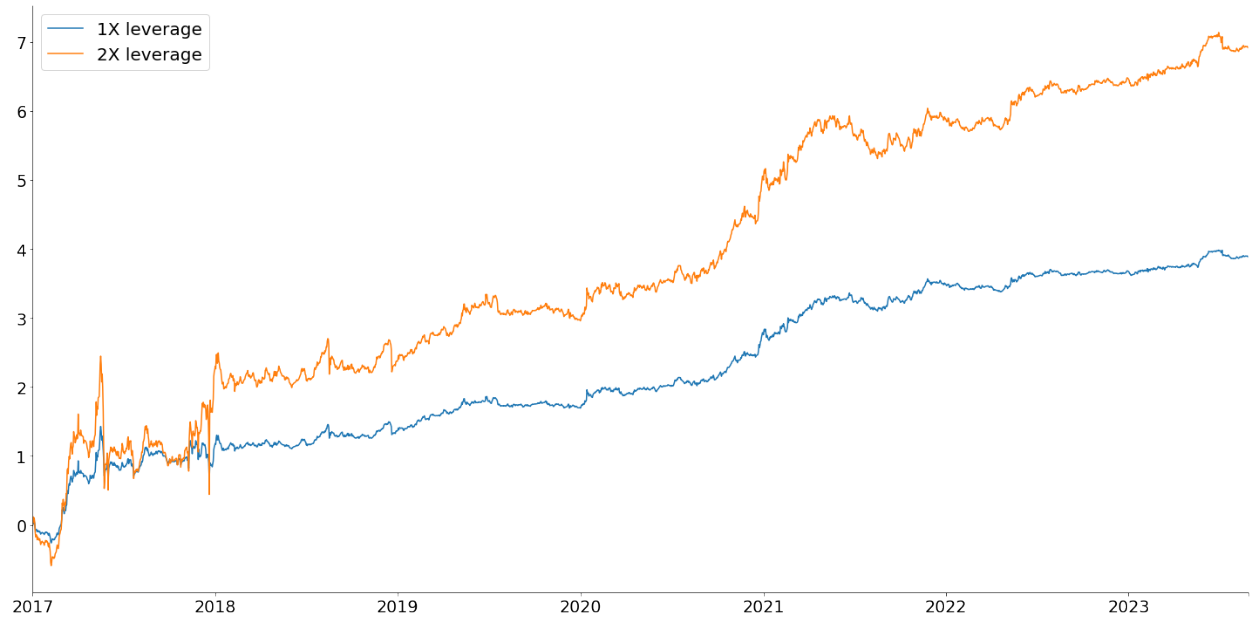


Figure 13: The (14, 7) cross-sectional momentum portfolio cumulative returns under different leverage levels

not be forgotten that the result is based on the best-case scenario. Many portfolios in our empirical study are liquidated under the cross-margin mode.

5.3.6 Reversal portfolios

Since the regression analysis using all coins suggests reversal, we test reversal strategies. Most reversal portfolios are liquidated during the bull market in early 2017. Therefore, we test them from the beginning of 2018. The performance of the reversal strategies is reported in the Internet Appendix (Tables IA15 to IA17 and Figures IA14 to IA17).

All the long-short portfolios with a holding period of less than a week yield a negative mean return. The portfolios with look-back and holding periods longer than 40 days yield positive mean returns, but only two of them earn positive profits. These portfolios, (49, 42) and (56, 42), outperform the market both yielding a Sharpe ratio of 0.57 (market Sharpe ratio = 0.37). Nevertheless, they yield negative returns for a prolonged period until early 2021. Although there appears to exist long-term reversal, constructing a profitable strategy based on long-term reversal is difficult. Unlike the momentum portfolios, even the long-only portfolios earn negative profits. The short-only portfolios perform even worse. Regardless of the strategy, momentum or reversal, taking a short position in the cryptocurrency market is extremely risky due to rather frequent large jumps.

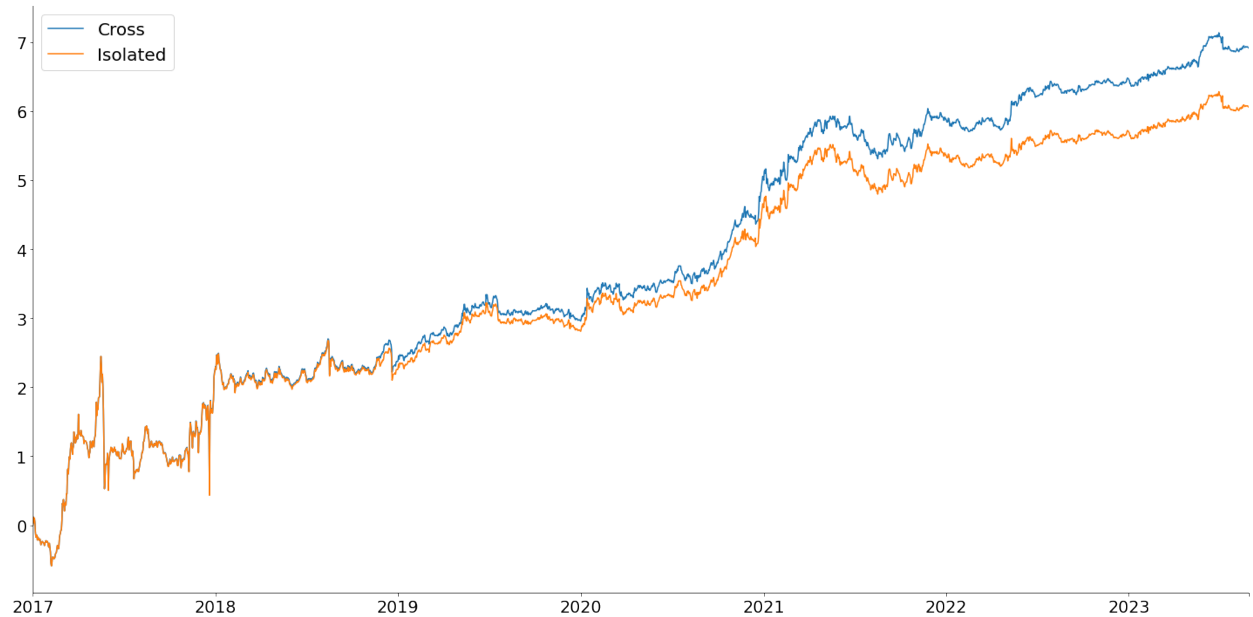


Figure 14: The (14, 7) cross-sectional momentum portfolio cumulative returns under different margin modes

The results contradict earlier regression results, in which the coefficients are more significant when the look-back and holding periods are short. These seemingly contradictory results can be attributed to the fact that the portfolios are value-weighted. Among large coins, the reversal effect is stronger when the look-back and holding periods are longer as shown in Table 13. The transition probabilities discussed in Section 5.2.5 confirm this view. Higher transaction costs due to more frequent rebalancing also contribute to the poor performance of a short-term reversal strategy.

6 Conclusion

We conduct a comprehensive analysis of both time-series and cross-sectional momentum in the cryptocurrency market, accounting for real-world considerations and assessing performance more accurately. We find some evidence of momentum, especially in the time series. However, momentum profits mostly originate from the long leg and the short leg inflicts significant losses on the strategy posing a threat of liquidation. A momentum-based market-neutral strategy that can generate stable profits appears unattainable. The maximum Sharpe ratio we obtain from a momentum strategy is about 1.5. Considering the high tail risk, the small number of liquid coins, and the high dominance of a few major coins, it is questionable whether a cryptocurrency momentum strategy can be qualified as an alternative investment vehicle for institutional investors. Moreover, we introduce a data-snooping bias by examining various pairs of look-back and holding periods, and the findings in this paper should be considered a best-case scenario. The cryptocurrency market is still immature and fast-evolving. The conclusion of this paper may be overturned in the future when the market becomes mature and more data are accumulated.

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A Appendix

A.1 Jump-diffusion parameter estimation

The parameters of the jump-diffusion process are estimated via a constrained maximum likelihood estimator (MLE) as described below.

$$\begin{aligned}
&\max_{\theta} \sum_{t=1}^{T} \log f(l_t;\theta) \\
&\text{subject to} \\
&E[l_t] = \mu - \frac{\sigma^2}{2} - \lambda k + \lambda\nu = \bar{l} \\
&Var[l_t] = \sigma^2 + \lambda\delta^2 + \lambda\nu^2 = \bar{v} \\
&Skew[l_t] = \frac{\lambda(3\delta^2\nu + \nu^3)}{(\sigma^2 + \lambda\delta^2 + \lambda\nu^2)^{3/2}} = \bar{s} \\
&Kurt[l_t] = \frac{\lambda(3\delta^4 + 6\nu^2\delta^2 + \nu^4)}{(\sigma^2 + \lambda\delta^2 + \lambda\nu^2)^2} = \bar{k},
\end{aligned} \tag{18}$$

where $\theta = \{\mu, \sigma, \nu, \delta, \lambda\}$, and $\bar{l}, \bar{v}, \bar{s}$, and $\bar{k}$ are the first four sample moments. The density function $f(l_t;\theta)$ is given by

$$f(l_t;\theta) = \sum_{i=0}^{\infty} \frac{e^{-\lambda}\lambda^i}{i!} N\left(l_t; \mu - \frac{\sigma^2}{2} - \lambda k + i\nu, \sigma^2 + i\delta^2\right), \tag{19}$$

where $N(\cdot)$ denotes a normal density function.

We impose the moment constraints because the usual MLE does not have a unique maximum and the moments of the estimated process, particularly skewness and kurtosis, are often significantly different from the sample moments. For the simulation in Section 2.2, we use the daily log return time series of the (14, 7) cross-sectional momentum portfolio. Below are the estimation result.

Sample moments			Estimation			
	r_t	l_t	$\hat{\theta}$		Estimated moments	
mean	0.00479	0.00285	μ	0.00477	mean	0.00285
std	0.07166	0.06004	σ	0.03200	std	0.06003
skew	14.44195	1.80449	ν	0.05096	skew	1.80338
kurt	466.26990	94.32867	δ	0.39418	kurt	94.13231
			λ	0.01633		